The impact of socioeconomic and cultural differences on online trade*

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Abstract: We use eBay data to investigate how trade in the U.S. is influenced by between-state differences in socioeconomic characteristics, tastes, and trust. States' similarity in cultural characteristics (ethnicity, religiosity, and political behavior) is predictive of online trade patterns. This is partly due to correlation between cultural markers and consumers' tastes. Consumers are also less likely to trade with dissimilar partners who lack extensive reputations or certification, which suggests that consumers infer seller trustworthiness from cultural similarity. There is no correlation between cultural similarity and buyer satisfaction, however, suggesting that perceived differences in trustworthiness are not validated by actual transactions.

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1. Introduction

An extensive literature documents that cross-border exchange of goods and services is greater between counterparties when they are closer together, whether in terms of physical, cultural, legal, or other "distance."[1]

While these empirical patterns have generated many insights into the drivers of global trade, the focus on cross-border transactions can make it challenging to distinguish among the various factors that could generate the positive correlation between trade and proximity. Closeness (whether geographic, cultural, or otherwise) may lead to greater exchange by reducing shipping costs, asymmetric information, and/or contracting frictions. At the same time, closeness may also reflect demand-based similarities, which can come from consumers' tastes or from firms' demand for intermediate goods. As a way of holding some of these factors constant, a handful of papers have looked at trade within a single country (e.g., Hillberry and Hummels 2008) or even within a single trading platform (Hortacsu, Martinez-Jerez, and Douglas 2009). These have tended to focus on geographic proximity, which is potentially correlated with a range of other "distance" measures.[2]

In this paper, we use eBay transaction data for U.S. buyers and sellers to explore how proximity – geographic, as well as cultural and socioeconomic – affects trade. Key features of this setting enable us to focus our attention on a subset of potential mechanisms and provide new insights on the determinants of trade. Because all of the transactions take place on the same platform and are governed by the same laws, we hold constant many of the institutional factors that vary across international boundaries. As a platform that directly connects individual buyers to sellers, eBay allows us to focus on *consumer* responses to

[1] See Anderson and van Wincoop (2004) for a summary of the earlier academic literature on distance and trade costs. The relationship between distance and trade is also debated in business and policy circles, and has generated interest in writing for the general public. See, for example, the contrasting perspectives in Friedman's (2005) *The World is Flat,* targeted at a general audience, versus Ghemawat's business-focused "Distance Still Matters" (2001) and "Why the World Isn't Flat" (2007).

[2] An important exception is Guiso, Sapienza, and Zingales (2009), who argue that cultural differences critically impact trust and therefore trade.

socioeconomic and cultural similarities and differences.[3] Prior work investigating these relationships has, for the most part, examined the combined trade in intermediate and final goods. Furthermore, eBay's product category structure, together with the detailed transactional data we employ, enables us to develop measures of congruence between the product preferences of consumers in a given area and the products supplied by sellers in other areas. Thus, we can examine the degree to which distance correlates with differences in tastes. Finally, because eBay has several well-established (and well-documented) mechanisms for identifying high-quality sellers, we can explore how socioeconomic and cultural distance influence trade for transactions that involve sellers that vary in their performance records (and hence the perceived riskiness of the transaction from the consumer's perspective). These features allow us both to control for the degree to which cultural or socioeconomic distance reflect divergent product preferences rather than simply perceived advantages from dealing with more trustworthy counterparties, and to compare the importance of these factors in settings in which trust is more or less important.

In this paper, we analyze monthly interstate trade in 2015 and 2016. As proxies for cultural distance (i.e., differences in shared values and beliefs), we employ differences in state ethnic composition, voting behavior, and religiosity; we also account for differences in a range of socioeconomic characteristics, such as income, urban share, and average age. Using standard controls for geographic distance, plus fixed effects for buyer and seller states by month, we find that greater cultural distance between two states is associated with significantly lower trade. These results suggest, for example, that if the ethnic similarity of New Mexico and Mississippi became as similar as that of Vermont and Maine, trade between these states would increase by about 56 percent. Other socioeconomic characteristics are also predictive of trade: our estimates suggest that shrinking the gap in home values between West Virginia and California to that of Tennessee

[3] An eBay seller's location is a prominent feature of each eBay product listing. Although information about the seller's buying and selling history on the eBay platform is available to buyers (and summarized in several reputation metrics), information about the seller's gender, ethnicity, or socioeconomic status is generally unavailable. Sellers use pseudonyms on the platform, making it difficult to infer these attributes from names. Furthermore, nearly all contact with sellers occurs via electronic communication. We believe, then, that any inferences buyers make about socioeconomic and cultural proximity or distance with sellers come from their beliefs about the expected characteristics of sellers at the designated location.

and Missouri, for example, would lead to an 11 percent increase in trade. These substantial associations between socioeconomic and cultural variables and trade could be due to greater trust between buyers and sellers, more strongly shared tastes between them, or a combination of the two.

Focusing first on the role of tastes, we construct two between-state measures of “taste overlap” that aim to capture the congruence between the products that eBay users in one state generally sell, and the products that users in another state generally buy. To construct these measures, we calculate the cross-category distribution of goods sold and the cross-category distribution of goods purchased in each state. Our first measure is based on differences between buyer states’ and seller states’ shares of activity in individual product categories. This distance measure decreases, for example, as the fraction of purchases in the electronics category in the buyer’s state approaches the share of sales of electronics from the seller’s state. The second measure is (one minus) the cross-product of the two category shares, which captures the likelihood that a randomly selected buyer from the buyer state is looking to purchase a product listed by a randomly selected seller from the seller state. To our knowledge, this approach to capturing congruence between consumers' tastes and sellers’ offerings is new to the trade literature, and we view it as a contribution itself.[4]

We find that both of our taste overlap measures are predictive of state-pair trade. Furthermore, the inclusion of one or both taste overlap measures has a large effect on the estimated coefficients for our cultural and socioeconomic variables. For example, the coefficient on our measure of states’ ethnic similarity is reduced by 35 percent when we include the category differences-based taste measure. A second measure of cultural distance – vote share for the winning candidate in the 2016 Presidential election – shrinks by more than half. Some of the reluctance to trade between dissimilar partners, therefore, is due to simple asymmetries in what products sellers offer and those buyers demand.

[4] Prior work, such as Guiso, Sapienza, and Zingales (2009), has accounted for taste overlap by incorporating correlations between consumption patterns in buyer and seller locations, rather than correlating the offerings of sellers and the purchases of buyers.

We next explore whether the correlation between sociocultural proximity and trade is the result of greater trust. We are motivated to do so by the large body of research on in-group favoritism dating back at least to Tajfel et al. (1971), and more recently work which shows that individuals place greater trust in others with whom they share common traits (Foddy et al. 2009, DeBruine 2002).[5] Our test is based on the insight that, if social and cultural similarity leads to greater trust, then quality-assurance mechanisms – which serve as an alternative source of trust – may moderate the impact of cultural and socioeconomic similarity. We explore this possibility by examining whether the effect of cultural and socioeconomic variables on trade is different for sellers with eBay's Top Rated Seller (eTRS) designation, which plausibly serves as an alternative signal of trustworthiness. Intuitively, we expect that trust between groups will matter less if there is a separate source of quality assurance (see Elfenbein, Fisman, and McManus 2012; 2015). Consistent with cultural similarity serving as a source of trust, we find that the correlations between trade and our cultural similarity variables (e.g., similarities in ethnicity and political affiliation) are substantially diminished for eTRS listings. We find a similar pattern when we separate sellers into high- and low-feedback groups,[6] which reinforces the notion that cultural similarity is especially important for trade when sellers do not yet have track records of previous success to reassure buyers of their reliability.

Finally, we examine the relationship between cultural similarity and buyer satisfaction with completed transactions. We measure satisfaction using two standard metrics: the fraction of all transactions that lead to positive feedback, and the fraction of feedback that is negative. We find no association between favorable feedback and cultural similarity. This could occur if buyer selection adjusts trade volume in a precise way across state pairs, so that consummated trades capture only the instances in which buyers find

[5] Research on trust games more generally is more ambiguous on the relationship between social distance and trust. Buchan et al. (2006), for example, find that this relationship depends on cultural context, with strong in-group effects in the U.S. but not in Asian countries, while Fershtman and Gneezy (2001) find that both Ashkenazi and Eastern Jews in Israel exhibit lower trust of Eastern Jews. Glaeser et al (2000) find no statistically significant relationship between demographic similarity and trust.

[6] The feedback score is one of the principal reputation mechanisms that eBay has used since its early days, and has featured in many studies; see Bajari and Hortacsu (2004) for survey. The literature has generally concluded that buyers see greater risk in dealing with sellers with low feedback scores, because their trustworthiness is more uncertain.

sufficiently trustworthy sellers. Perhaps more plausibly (if some fraction of buyers are inattentive to the seller's state and its attributes, or if individuals exaggerate stereotypes based on coarse observables as in Bordalo, Coffman, Gennaioli, and Shleifer (2016), it suggests that perceived trustworthiness (untrustworthiness) of sellers in culturally similar (different) states is not validated by executed transactions.[7]

Our paper provides three contributions. First, we document that cultural distance – as measured by differences in ethnicity, religiosity, and voting behavior – is negatively associated with trade patterns in an online market in which buyers choose among sellers with observable locations but whose personal identities are effectively concealed. These differences are robust to controlling for socioeconomic differences and measures of taste overlap. This, in and of itself, is somewhat surprising as buyers and sellers in this marketplace do not meet directly, see pictures of one another, or engage in voice communication. Our second contribution is to show that socio-cultural similarity matters more for trade when there is more uncertainty about the quality of the seller, suggesting that buyers associate socio-cultural similarity with greater trustworthiness. In examining customer satisfaction with executed transactions, we raise the question of whether these perceptions of trustworthiness are accurate or driven by mistaken beliefs about the impact of buyer-seller differences. Finally, we see our taste overlap measures, which explain a significant share of interstate trade on eBay, as a methodological contribution that could be applied to cross- or within-country trade models.

While our work contributes broadly to the literature on cross-country trade, the clearest antecedent is Hortacsu, Martinez-Jerez, and Douglas (2009), who study the effect of buyer-seller distance on trade for eBay transactions, and also for a similar Latin American platform, Mercado Libre. Like us, they find a much smaller distance effect relative to gravity models estimated using trade in both intermediate and final goods (whether for cross-state or cross-country trade). They further provide an indication that tastes play

[7] This is also consistent with the findings of DeBruine (2002), who finds that, while individuals exhibit greater trust in others with similar facial features to themselves, individuals are no less likely to betray facially similar partners.

some role for “local” preferences, by showing that the distance effect is particularly prominent for sports memorabilia and tickets. Our agenda is distinct from Hortacsu, Martinez-Jerez, and Douglas (2009) in that our aim is to understand not just the geographic distance effect but rather the broader set of similarities and differences between populations that impact trade. Perez-Truglia (2017) also deploys eBay data to study the development of trust among buyers. He finds that more experienced buyers on the platform are less likely to give negative feedback, which he interprets as an indication of growing trust in sellers. Feedback is unaffected by (county-level) measures of pro-social beliefs (e.g., belief that others are honest). Thus, as in our work, Perez-Truglia studies the determinants of trust, but differs in that his focus is on buyer attributes rather than buyer-seller distances.

Our interest in the effects of cultural and social distance on trade is shared by Guiso, Sapienza, and Zingales (2009), who study the link between bilateral trust among European nations and economic activity such as trade and investment. They find that, particularly for “trust-sensitive” differentiated products, trust impacts trade flows. As noted at the outset, while these cross-country patterns are extremely helpful in guiding our understanding of the determinants of trade, we are able to hold many more factors constant in looking at trade on a particular platform within a single country. In a paper closely related to our own, Bailey et al. (2018) examine social-media friendships on platforms such as Facebook, and they documents that trade between counties correlates with measures of social connectedness. Our work explores similar socio-cultural determinants of commercial interactions, but allows us to investigate distinct mechanisms.

These papers fit into a much broader literature on the determinants of trade flows. While most work in this area uses cross-country panel data, Hillberry and Hummels (2008) looks at the flow of goods within the U.S. Their focus is on understanding the very strong geographic distance effect, and their explanation centers on production co-location and trade in intermediate goods. In that sense, we see our focus on consumer goods and preferences as complementary to their work.

Finally, our work connects to a relatively new literature on habit formation, taste, and the geography of consumption, pioneered Bronnenberg, Dhar, and Dubé (2007) in a study showing that brand preferences are heavily influenced by the distance of consumers from where the company was founded. Bronnenberg, Dubé, and Gentzkow (2012) and Atkin (2013) extend this framework to show that consumers maintain loyalty to a brand (and in the case of Atkin, food type) even when they migrate. Both of these latter papers naturally have taste-based implications for the flow of goods within a country.

2. Data

We use two broad types of data in our analysis. The first is aggregated sales data from eBay, including information on state-to-state trade in the U.S. and distributions of U.S. buyer and seller transactions across product categories. The second is state-level demographic data, drawn from a variety of sources we describe below, which capture cultural and socioeconomic characteristics of individual states.

2.1 eBay data

Our eBay data come from the firm's U.S. platform, which hosted over $24 billion worth of transactions during 2017. eBay.com is the ninth-most frequently visited website in the U.S., behind only Amazon among e-commerce platforms.[8] eBay offers its users the opportunity to sell items in several formats, and it attracts sellers who vary widely in their engagement with the platform. Some sellers offer items for sale rarely, while other sellers are professionals who create dedicated "eBay Stores." Seller quality and other attributes are tracked in a variety of ways. All sellers have at least a small amount of information visible to consumers, including a feedback score and the location (city and state) from which an item will ship. The feedback score reports the sum of individual-transaction feedback (+1, 0, or -1) that an eBay user has received as a seller on the platform. In addition, a small fraction of sellers (who represent a disproportionately large proportion of sales volume) earn an eTRS badge, which indicates that they have cleared specified thresholds for sales volume and customer satisfaction. These reputation mechanisms have been studied extensively in the economics literature. Cabral and Hortascu (2010), Hui, Saeedi, Shen, and Sundaresan (2016), and Elfenbein, Fisman, and McManus (2015), provide empirical evidence of the impact of these mechanisms

[8] Web traffic statistics are from the marketing firm Alexa (an Amazon.com subsidiary), accessed on March 1 2018.

on sales probability and price, while Hui, Saeedi, Spagnolo, and Tadelis (2018) examine the mechanisms' impact on seller entry, and Nosko and Tadelis (2015) study how buyers learn from experience about the overall quality to be expected on the platform.

When an eBay consumer searches for a product, the platform provides the user with a collection of listings sorted by several factors, including product characteristics, price, sellers' quality ratings, and sellers' physical proximity to the consumer. The consumer may elect to re-sort the listings based on a single factor, including proximity. (Other than geography, consumers cannot filter or sort listings based on the difference measures we use in our analysis below.) eBay sellers can affect their positions in search results through their choices of prices or shipping fees, but they are largely unable to affect the geographic distribution of consumers who evaluate their products. eBay consumers, therefore, have ample opportunities to inspect products from all over the United States, and interstate trade patterns are likely to reflect consumers' choices over trading partners rather than awareness of partners, which can be an important driver of geographic trade patterns in other contexts.

We collect data on eBay transactions in which both the buyer and seller identify themselves as located in the U.S. In addition, we limit the population of sellers to those who do not operate eBay Stores. We apply this filter on sellers for two reasons. First, sellers with eBay Stores may ship from warehouses that are not in the same state as the seller, which creates uncertainty about how to classify the seller's location. Second, we conjecture that buyers are more likely to use state characteristics to infer seller attributes when the seller provides only the sparse personal information offered in eBay's standard format, whereas sellers with Stores often use the interface to provide additional information about themselves. While the subset of sellers we study are likely less professional than those with eBay Stores, many sellers in our sample have earned eTRS status or have relatively large feedback counts.

2.1.1 Measures of inter-state trade and customer satisfaction

Our primary eBay data comprise a comprehensive monthly record of transactions that occurred between January 2015 and December 2016. For the U.S.-based buyers and sellers described above, we observe the total quantity of items sold and total dollar revenue from product sales, excluding shipping fees, between each pair of U.S. states; we also observe buyer and seller transactions for Washington D.C., which we treat as a separate (51^{st}) state in our analysis. In addition to the aggregate monthly transactions, we observe transactions categorized according to the sellers' eTRS statuses (badged or not) and whether their feedback scores were above or below 200 at the time of the transaction.[9] We define *High feedback* to denote a seller that has feedback of at least 200. This is a relatively low feedback threshold, as we aim to distinguish the sample split based on feedback from the split based on eTRS.[10] Roughly half of all sales revenue (48%) and transactions (45%) associated with feedback above 200 is from sellers without eTRS certification. Thus, these two different sample splits provide somewhat correlated, but not identical, tests.

Finally, we calculate average monthly feedback provided by buyers, aggregated to the state-pair level. Our main measure is Effective Percent Positive (EPP_{bst}), the fraction of total transactions between buyers in state b and sellers in state s during month t that leads to positive feedback. This measure is proposed by Nosko and Tadelis (2015) to deal with the fact that, conditional on feedback being provided, it is almost always (99.3%) positive. They show that there is information on seller reliability in the fraction of buyers that provide any feedback (which averages approximately 65% in their sample). We use the fraction of transactions with negative feedback ($Negative\ feedback_{bst}$), conditional on feedback being provided, as an alternative measure of buyer satisfaction.

In preparing the data, we exclude observations on trade that occurs within states because these cases have zero "distance" in almost all of the measures that we introduce below. We provide summary statistics on state-to-state monthly trade in Table 1. Trade between states (exclusive of shipping) has a mean monthly value of $365,132 in total for 9121 items (medians of $110,971 and 2924 respectively). In our sample, which conditions on less-professional sellers by excluding data from eBay Stores, state-level sales

[9] For example, we may observe that, during March 2016, Arizona sellers sold 200 items for $2000 (in total) to Missouri buyers. Within those 200 items, 80 with a value of $700 were from eTRS sellers, and 125 items with a value of $1400 were from sellers with feedback greater than 200.

[10] We have also performed the analysis after separating sellers by whether their feedback is greater than 1000. Our results are very similar to those reported below for a feedback threshold of 200.

by non-eTRS sellers have an average value that is 65% greater than that of eTRS sellers; the quantity sold by non-eTRS sellers is 23% greater. The sales value associated with low-feedback sellers is about half of that associated with sellers with feedback above 200. The average EPP_{bst} value across state dyad-month combinations is just over one half, and the mean rate of negative feedback is 0.36%.[11]

As expected, pairs of large states have the greatest transaction volume; each of the top ten dyads in monthly revenue involve California buyers and New York sellers. The only other states that appear in the next ten dyad-months are Florida (4 times) and Texas (once). When we rank monthly trade by quantity rather than revenue, the top ten all involve Florida or Texas buyers and California sellers. States with low trade volumes include Alaska, Rhode Island, Vermont, Washington, D.C., and Wyoming.

2.1.2 Measures of overlap between purchases of buyer states and sales of seller states

We supplement the trade flow data with additional information from eBay on the distribution of transactions across 33 high-level product categories (e.g., Consumer Electronics, Collectables and Art, Home and Garden, etc.). For each combination of buyer state (b), seller state (s), and product category (c), we obtain the total quantity of items sold and the associated revenue during 2015-16. Let q_{bsc} represent the quantity of items sold in a (b, s, c) combination. For each b and s pair, we calculate:

$$q_{b,-s,c} = \sum_{s' \in S \setminus s} q_{b,s',c} \quad \text{and}$$

$$q_{b,-s} = \sum_{c} q_{b,-s,c}\,.$$

The notation $S \setminus s$ indicates the set of all states excluding state s. We use these objects to calculate

$$\sigma^{q}_{b,-s,c} = \frac{q_{b,-s,c}}{q_{b,-s}}$$

[11] The difference between our mean EPP value and the 65% rate reported by Nosko and Tadelis (2015) may be due to differences in our respective samples' seller populations; they take a platform-wide average that includes professional sellers that we largely omit.

as the share of b's quantities that is in category c, excluding any trade between b and s. The vector $\sigma^q_{b,-s}$ contains $\sigma^q_{b,-s,c}$ values for each category. For an individual buyer state we obtain 50 versions of $\sigma^q_{b,-s}$ (one for each $s \neq b$; recall that we include Washington D.C. as a 51st state), but they are all quite similar to each other because removing a single trading-partner seller-state (which we do to avoid a mechanical correlation between our taste overlap measures and realized buyer-seller state transactions) generally has a small impact on the distribution of buyer activity across categories within a state. We produce analogous "leave-out" measures for three additional variables: buyer-state revenue (r) across categories, which generates $\sigma^r_{b,-s}$ values, and for quantities and revenues while focusing on the distribution of items sold from state s. Let the seller-focused share vectors be $\sigma^q_{s,-b}$ and $\sigma^r_{s,-b}$.

We use these distributions to construct taste difference measures that aim to capture the divergence between states in the products they buy and sell. For each pair (b, s) and each transaction variable ($j = q$ or r), we compute a "cross-product category difference" measure, P, as one minus the cross-product of category shares:

$$P^j_{b,s} = 1 - \sum_c \sigma^j_{b,-s,c}\sigma^j_{s,-b,c}.$$

$P^j_{b,s}$ is similar to a Herfindahl index in which (b, s) pairs replace squared market shares; we subtract the summed products from one so that it is increasing in distance. When the buyer and seller states both have large fractions of their activity in very different categories (i.e., the two states have very different category tastes), $P^j_{b,s}$ will be relatively large. We rescale the measure to have mean zero and standard deviation one, to make its estimated impact easily comparable to other variables.

We use a Euclidean distance calculation to develop an alternative measure of the differences between items that are sold in a seller state and items that are purchased in a buyer state. The variable D captures "Euclidean category distance," and we compute it as

$$D^j_{b,s} = \sqrt{\sum_c \left(\sigma^j_{b,-s,c} - \sigma^j_{s,-b,c}\right)^2}.$$

As in the case of $P_{b,s}^{j}$, we calculate $D_{b,s}^{j}$ at the quantity (j = q) and revenue (j = r) level, and we again normalize the variable so that it has mean of zero and standard deviation of one. The measures $P_{b,s}^{q}$, $P_{b,s}^{r}$, $D_{b,s}^{q}$ and $D_{b,s}^{r}$ capture different aspects of trade and handle between-state differences in distinct manners, particularly in how they are affected by buyer and seller category dispersion. A buyer-seller pair with high, but similar, dispersion across categories will have a low value for the Euclidean category distance but a large value for the cross-product category difference. Thus, while both measures capture some intuitive element of overlapping category interests, in some cases the two measures may be negatively correlated. In practice, however, once one controls for differences in average levels of $P_{b,s}^{j}$ and $D_{b,s}^{j}$ across states, the correlation between the two measures is strongly positive.

2.2 Demographic data

Table 2 reports summary statistics for the state-level data we use to create measures that capture differences in socioeconomic and cultural characteristics across states. We draw data on *Median household income*, *Share with bachelor's degrees and above*, *Median age*, *Share of males*, *Share in urban areas*, *Home ownership share*, and *Median home value* from the 2015 American Community Survey, which is organized by the US Census. The ACS interviews a representative sample of over two million Americans each year, providing a high-quality source of data with broad geographic coverage. We aggregate responses at the state level to generate state-level measures of these variables.

State-level data on *Religiosity* are drawn from a survey conducted by Pew Center's US Religious Landscape Center Research, which was reported in 2016.[12] Pew reports data on the percentage of adults in a state who say that religion is very important in their lives, the percentage who say they pray daily, the percentage who say they attend worship services at least weekly, and the percentage who say they believe

[12] http://www.pewresearch.org/fact-tank/2016/02/29/how-religious-is-your-state [accessed 2/23/2018]

in God with absolute certainty. They combine these measures in an overall index, which we use as our measure of religiosity.

We measure similarity in political attitudes using voting patterns from the 2016 U.S. presidential election, taken from the Federal Election Commission. We calculate the proportion of votes cast in each state for the winning candidate as a fraction of the total votes cast for the two major parties, and label this variable *Winner vote share*.[13] In creating cross-state difference measures of the variables described above, we simply take the absolute value of the difference between the buyer and seller state values. We report summary statistics for these cross-state difference measures in Table 3.

We report two additional measures at the state dyad level in Table 3: *Distance* and *Ethnic difference*. *Distance* is the distance (in kilometers) between the state capitals, computed using a "shortest curve" method.[14] Finally, we use the ACS data from 2015 on ethnicity to construct a measure of ethnic similarity between two states. The variable we construct is analogous to a between-group measure of ethnic fractionalization (see, e.g., Alesina et al. 2003) which aims to capture the likelihood that a person chosen at random from the seller state is in the same ethnicity category as a person chosen at random from the buyer state. Let S_E^i be the share of individuals in the ethnic category E of state i, which is drawn from a set of mutual exclusive and collectively exhaustive categories provided by the ACS. We then calculate the ethnic dissimilarity between seller state s and buyer state b as *Ethnic difference*$_{bs}$ = $1 - \sum_{all\ E} S_E^b\, S_E^s$. A higher level of this measure indicates a higher likelihood that two people drawn at random from each state are of different ethnicities.

[13] We focus on 2016 vote shares to measure political preferences because it is based on real stakes decisions during the same period covered by our eBay transactions data. For robustness, we considered two alternative measures of between-state differences in political preferences. The first is based on the winner vote share in 2012. The second is constructed using survey responses from a 2015 Gallup Poll of 175,000 adult Americans on their political views. The raw correlations among our three state-level measures of political preferences are each above 0.93; if we use 2012 election data or Gallup survey responses to measure political differences across states, our results are qualitatively similar to those based on the most recent election data.

[14] Alternative distance measures yield near-identical results, which is unsurprising given the very high correlation across such measures. For example, the correlation between the log of the distance between capitals and the log of the distance between population centers is 0.995.

In the summary statistics in Table 3, we present the raw difference measures. However, to make the effect sizes more easily comparable across distance measures in our empirical analysis in the next section, we normalize all cultural and demographic distance variables to have a mean of zero and standard deviation of one.

3. Empirical Analysis and Results

Our main specification takes the form:

$$\log(Trade_{bst}) = \Gamma C_{bs} + \Theta X_{bs} + \Upsilon T_{bs} + \beta \log(Distance_{bs}) + u_{bt} + v_{st} + e_{bst} \quad , \quad (1)$$

where C is a vector of our set of cultural similarity variables, X a vector of socioeconomic similarity variables, T contains our taste overlap variables (P and D), $\log(Distance)$ is logarithm of the distance between the two states' capitals, and u and v are buyer state $\times$ month and seller state $\times$ month fixed effects respectively. We employ both quantity- and revenue-based measures of monthly $Trade_{bst}$ between seller state s and buyer state b during month t. As described in Section 2, the set of variables we use to capture cultural/attitudinal factors include ethnic difference as well as pairwise absolute differences in the fraction of each state's level of religiosity and vote share in 2016 Presidential election. The set of socioeconomic variables we use are (absolute) differences in median income, share with bachelor's degree, median age, male share, median home value, and shares of urban residents and owner-occupied housing, each normalized such that the mean difference between states is 0 and the standard deviation is 1. We use two-way clustering by seller state and buyer state to calculate the standard errors.

3.1 Impact of cultural and socioeconomic differences on inter-state trade

In Table 4, we show our baseline findings for both value- and quantity-based measures of state-pair trade. In the first three columns, we present results that use the log of total sales revenue as our measure of trade. In columns 1 and 2 we include the "culture" variables and the socioeconomic variables separately, and we include both groups of covariates in column 3. Focusing first on the set of measures that reflect cultural differences, we find in column 1 that all three “distance” measures are predictive of trade, in the expected directions: the coefficients on the ethnic, political, and religious distance measures are all negative and significant at the 1 percent level.

Given that these variables are all normalized to have standard deviation of one, their coefficients are easily interpreted and compared. By far the biggest effect comes from ethnic difference: a one standard deviation increase in ethnic difference is associated with a 12 percent decrease in state-pair trade. The coefficients on religious and political differences imply sizeable but more modest effects.

Turning to the socioeconomic variables, their role in predicting state-pair trade is mixed. While similarity in urban share is predictive of trade in column 2, the inclusion of culture variables reduces the size of its coefficient by about half. Three of the socioeconomic variables remain significant predictors of trade in column 3: differences in male share, urban share, and home values. (While we group these variables with other demographic measures, there are no clear guidelines on whether buyers view particular measures as reflecting cultural versus other social differences.) None of these results appear to be driven by outlier observations – we observe similar patterns if we omit Alaska and/or Hawaii (both are obvious geographic outliers, and Alaska is also an outlier in male share).

We note that, as expected, all regressions produce coefficients on log(*Distance*) that are negative, economically important, and precisely estimated. The estimated coefficients that we find are larger, but similar in order of magnitude, to the estimates produced by Hortacsu, Martinez-Jerez, and Douglas (2009) for eBay trade.

Columns 4 through 6 present results from the same set of specifications, using the logarithm of monthly sales quantity as the outcome variable. The patterns are broadly similar though in most cases marginally weaker than the results that measure trade in terms of total transaction value.

Finally, we illustrate these results graphically, using a binned scatter plot (Hao et al, 2010) to display the relationship between the three main proxies for culture and interstate trade. To capture the role of all three culture variables simultaneously, we use the sum of (normalized) state-pair ethnic, religiosity, and voting differences. We group the data into 50 bins with equal numbers of observations, though in practice the patterns are essentially the same if we use coarser (e.g., 25 bins) or finer (e.g., 100 bins) groupings. Finally, we residualize the data, netting out the effects of all control variables included in our main specification (Table 4, column 3), including buyer-state×month and seller-state×month fixed effects, u_{bt} and v_{st}, respectively.

We present the resulting binned scatter plot in Figure 1, which shows a clear negative correlation between our summary measure of state-pair cultural distance and interstate trade.[15] The relationship is roughly linear, and it is in line with the estimates presented in Table 4. A one standard deviation decrease in our aggregate cultural difference measure (1.84) is associated with a 5 percent increase in interstate trade, an effect that lies between the various coefficient estimates on the roles of differences in ethnicity, religiosity, and voting in Table 4. In Appendix Figures A1 – A3, we present binned scatterplots for each individual cultural difference variable, generated while including all other controls from Table 4, column 3 (e.g., in Figure A1, when we illustrate the role of ethnicity differences, we control for differences in religiosity and voting). As expected, given the more prominent role of ethnicity in our regression results, the plotted pattern is clearest and the best-fit slope is steepest in Figure A1, which uses ethnicity to measure cultural differences.

3.2 Accounting for differences in tastes between buyer and seller states

As noted from the outset, there are two primary reasons we might expect culturally or socioeconomically similar states to trade more: greater trust and shared tastes. In the next two tables, we present results that aim to explore the extent to which these factors account for the correlation between state-pair similarity and trade.

In Table 5, we present results that build on those in Table 4, including one or both of our taste overlap measures as controls. Intuitively, if the inclusion of direct taste measures attenuates the effects of

[15] The scatter plot is quite similar if we include only the fixed effects u_{bt} and v_{st}, as suggested by the stability of the coefficients across columns 1 and 3 of Table 4.

cultural or socioeconomic closeness, then we may infer that the initial correlation was capturing, at least in part, overlapping tastes. Focusing on total monthly sales revenue as our measure of trade, we explore how the inclusion of our direct measures of Euclidean category distance (D) and/or cross-product category differences (P) affect the estimates in Table 4. We begin in column 1 by showing the results from Table 4, Column 3, for comparison. We add Euclidean category distance as a covariate in column 2. Our category difference measure is itself highly predictive of trade ($p < 0.001$). A one standard deviation increase in Euclidean category distance is associated with a 27 percent reduction in state-pair trade. Moreover, the inclusion of category differences has a very large effect on the predictive power of our cultural variables: the coefficient on *Ethnic difference* falls by about 35 percent and the coefficient on *Voting difference* falls by more than half. One exception is the coefficient on *Religiosity difference*, which increases marginally in absolute value. The coefficient estimates for our socioeconomic variables are also attenuated, though the effect of controlling for category differences on these variables is less pronounced. Column 3 uses our cross-product category difference measure (P) to capture state-pair taste differences. The coefficients on our cultural difference variables are again attenuated. In column 4 we include both taste difference measures as controls. Interestingly, while the coefficient on each is smaller than its counterpart in columns 2 and 3, both measures remain significant at the 1 percent level, suggesting that these two measures effectively capture different types of variation in taste overlap. Again, most coefficients on our cultural similarity variables are markedly lower than in column 1. We show the analogous set of results with quantity-based measures of trade and taste overlap in Appendix Table A1. The patterns are broadly similar to those presented in Table 5, with one exception: the attenuation of the coefficients on *Voting difference* is much smaller, and these coefficients remain statistically significant when taste controls are added.

3.3 Quality assurance and the impact of cultural differences on trade

In Table 6, we turn to explore whether buyers deem sellers in states that are more culturally or socioeconomically different to be less trustworthy and hence trade less with them. Since we lack a direct measure of state-pair trust (the approach utilized by Guiso, Sapienza, and Zingales 2009, in studying

European trade flows), we use a different empirical approach. We first compare the importance of cultural similarity in determining trade, depending on whether the seller has earned a certification label that may substitute for trustworthiness, namely the eTRS designation. Intuitively, little trust is required on the buyer's part to purchase from a seller that has an excellent, certified track record for quality and promptness. Similarly, we posit that questions of trustworthiness are more salient for evaluating sellers that are new to the platform and have a limited observable track record as measured by feedback. To test whether cultural similarity matters more when dealing with these less-established sellers, we allow for different impacts depending on whether sellers have feedback scores greater or (weakly) less than 200 at the time of the transaction.

Table 6 contains results from three models. First, in column 1, we reproduce the results from Table 4's column 3 to facilitate a comparison between our main results versus those with the eTRS and feedback interactions. Second, we use columns 2a and 2b to report results from a single model that includes two observations per month and state-pair: one is aggregate sales by non-eTRS sellers and the other is aggregate sales from eTRS sellers. We allow measures of socioeconomic differences, taste differences, and geographic distance to affect each type of seller's transactions differently, and we implement this with a full set of interactions of the variables in column 1 with an indicator (*eTRS*) for whether trade involves an eTRS seller.[16] Table 6, column 2a shows the coefficient estimates for the direct effects of all state-pair variables, while column 2b shows the coefficient estimates for all variables' interactions with *eTRS*. Thus, the coefficients in column 2a show the effects of the state-pair differences when sellers lack eTRS certification, which forces buyers to depend on other information or characteristics to infer seller reliability. The coefficients in column 2b show the incremental effect for $eTRS = 1$ transactions, so that the total effect

[16] We also interact each state-month fixed effect with the eTRS indicator to account for different overall trade volumes flowing out of and into states by eTRS status. For example, if California consumers, on average, prefer eTRS items regardless of the item's origin, then this tendency is captured by the additional fixed effect for California buyers by eTRS status. Similarly, if Florida has a greater than average fraction of eTRS sellers shipping to all destinations, then the additional eTRS-specific seller-state fixed effect will account for this pattern.

for $eTRS = 1$ transactions is the sum of the coefficients in columns 2a and 2b. Columns 3a and 3b repeat this exercise, using *High feedback* rather than eTRS to divide sellers by their performance records.

While the estimates of the interaction terms in column 2b are imprecise, for our cultural difference measures they consistently go in the direction of implying that these differences matter less when buyers consider purchases from eTRS-badged sellers. As an intuitive test of whether the three variables collectively differ for eTRS versus non-eTRS sellers, we provide an F-test of the sum of their coefficients, which has a *p*-value of 0.006. (An F-test of the joint significance of the three separate coefficients has a *p*-value of 0.028.) The eTRS interactions with the socioeconomic variables are of inconsistent sign and an F-test of their sum has a *p*-value of 0.354. (Our analysis using a quantity-based measure of state-pair trade, shown in Appendix Table A2, yields qualitatively similar conclusions and stronger statistical support.) Together, these estimates suggest that, cultural differences have a greater dampening effect on trade between buyers and sellers who have not earned quality certification, relative to the effect of cultural differences on trade between buyers and sellers with quality certification.

The results in columns 3a and 3b corroborate those in 2a and 2b. In particular, the joint effect of cultural differences is significantly smaller for *High feedback* sellers: an F-test of the summed coefficients has a p-value < 0.001. Comparing the coefficients across columns 3a and 3b, our estimates suggest that the effects of ethnic and voting differences are more than halved for high feedback (relative to low feedback) sellers. The estimates in 3a and 3b also show similar patterns for socioeconomic differences as those in columns 2a and 2b, with the effect of these variables of inconsistent sign in both columns. Given that our data do not contain (near-) experimental variation in eTRS or feedback, we interpret these variables as capturing the effects of a range of markers or achievements that distinguish well-established sellers.

Collectively, we interpret the estimates in Table 6 as suggesting that cultural similarity supports trust, so that cultural distance becomes a greater determinant of trade when quality certification or extensive seller reputations are absent. This finding echoes that of Guiso, Sapienza, and Zingales (2009), who find that bilateral trust is a stronger predictor of trade for differentiated products relative to commodities.

3.4 Impact of cultural and socioeconomic differences on buyer satisfaction

In our final set of results, we examine whether, conditional on a transaction having taken place, cultural distance predicts buyer satisfaction. Even under the assumption that a random buyer-seller pairing leads to a better outcome between culturally proximate states, the theory is more ambiguous on this correlation, given buyer selection. Indeed, the most straightforward model that incorporates (correct) buyer expectations of seller trustworthiness would lead to no correlation between state-level attributes and buyer satisfaction. Although fewer transactions may occur between dissimilar states, those that are completed (and thus are eligible for feedback) may include only sellers who appear to be as reliable as those from more similar states. However, if buyers are not fully attentive to a seller's state and/or the implied cultural distance in examining a product listing, we would expect buyer satisfaction to decrease with distance, assuming their initial beliefs were well-founded.

In Table 7 we provide results based on a variant of specification (1), in which we use effective percent positive (*EPP*) and fraction negative feedback (*Negative feedback*) as measures of buyer satisfaction. Geographic distance between states is negatively and significantly related to *EPP*, and positively and significantly related to *Negative feedback*, which may reflect shipping-related issues. Columns (1) and (2) use *EPP* as a satisfaction measure, with taste overlap controls calculated using revenue and quantity, respectively. In these specifications, none of the cultural or socioeconomic distance measures approach significance. We obtain similar results using *Negative feedback* as an outcome measure in columns (3) and (4) – though *Voting difference* is in this case a significant (albeit quantitatively modest) predictor of negative feedback. A one standard deviation increase in *Voting difference* is associated with a 4 percent rise in the rate of negative feedback.

We recognize that, while our results are helpful in understanding how cultural differences shape trade, they do not provide a definitive interpretation. One explanation for the pattern of results we obtain (incorporating both the trade and satisfaction results) is that, while buyers' perceptions of trustworthiness are associated with cultural similarities or differences, these perceptions reflect excessively strong generalizations (e.g., Bordalo et al. 2016) which are not validated in practice. According to this interpretation, perceptions shape the propensity to transact, but do not reflect actual performance conditional on the transaction being executed. A second explanation is that selection drives the observed satisfaction results. Buyers choose to interact only with sellers that they deem sufficiently trustworthy, and make accurate inferences of trustworthiness based upon cultural similarities or differences. Observed transactions then lead to levels of customer satisfaction that are independent of buyer-seller cultural similarity. This possibility raises the question of whether sellers do, in fact, behave in a more trustworthy manner when interacting with buyers from states with culturally similar populations. Our results do, however, seem to rule out the possibility that buyers receive positive utility, akin to Andreoni's (1990) "warm glow" for charitable giving, from purchasing from a culturally similar seller. If that were the case, we would plausibly expect buyers to give more favorable ratings to culturally similar buyers. While further narrowing the range of interpretations is difficult given that we only observe realized transactions, we hope that in future work we may assess more directly whether cultural similarity facilitates actual trust, or merely the perception of greater trustworthiness.

4. Conclusions

We document a robust association between cultural (and to a lesser degree socioeconomic) similarities and inter-state trade on eBay. Our findings that these associations are attenuated by the inclusion of more direct controls for taste overlap, and that these associations matter more for trade with uncertified sellers or sellers with low reputation scores, together suggest that cultural similarity drives trade both because of greater overlap in tastes and higher trust. These findings contribute to a relatively small body of work that examines the relationship between socio-cultural similarity and trade, such as Guiso, Sapienza, and Zingales (2009) and Bailey et al. (2018).

The fact that we find these relationships on an e-commerce platform in which face-to-face contact is rare and demographic information about counterparties is concealed is, perhaps, surprising. While discrimination based on buyer or seller ethnicity has been documented on e-commerce platforms such as Airbnb (Cui, Li, and Zhang 2016; Edelman, Luca, and Svirsky 2017), on online classified advertisement platforms (Doleac and Stein 2013), and online used-car markets (Zussman 2013), features of the eBay platform make it nearly impossible to discover the ethnicity or other demographic details of a seller. Buyers in our setting must, therefore, make inferences about a seller based upon his or her location. Our results, which suggest a higher level of trust between more similar eBay users, indicate that eBay users – whether consciously or not – are incorporating such information in their purchasing decisions. Our observations about buyer satisfaction raise an important question about whether eBay buyers incorporate this information in an accurate way; however, we cannot answer this question in a definitive manner with our current data.

Finally, our results also point to some positive potential measures for stimulating trade between dissimilar partners: quality-assurance institutions and information about sellers' track records appear to help buyers trust sellers from locations different from their own. Given the emphasis placed by eBay and other two-sided platforms on developing robust customer feedback mechanisms, such markets may hold out the promise of reducing the importance of sociocultural distance in economic transactions.

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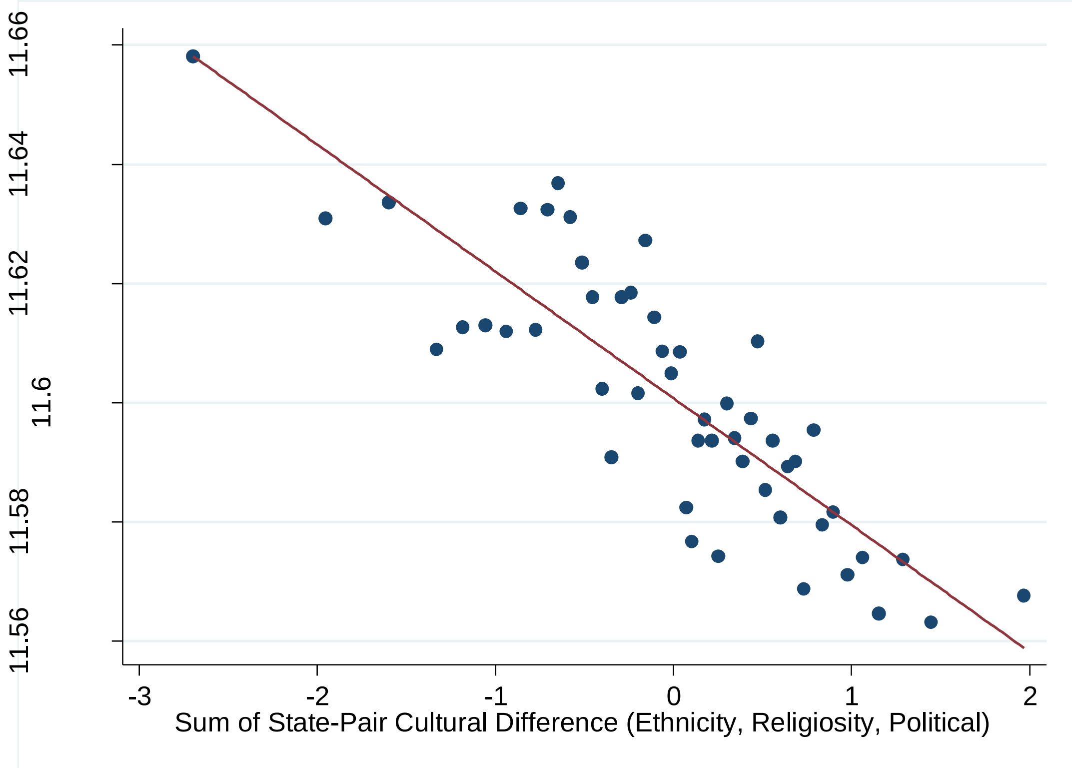
Figure 1: Relationship between cultural distance and interstate trade



Note: The figure shows a binned scatter plot to illustrate the relationship between state-pair cultural differences and interstate trade. The horizontal axis is the sum of the three measures of cultural distance: ethnicity, religiosity, and voting. We use 50 bins, and residualize the data to account for all control variables included in Table 4, column 3.

Table 1: State-to-state monthly sales and feedback

	Mean	Median	SD	Min	Max
Revenue	365132.5	110971.3	875954	255.28	18044242
Quantity	9120.58	2924	20635.9	7	386836
Revenue, non-eTRS sellers	227268.6	68625.57	545971.2	101.48	9900624
Revenue, eTRS sellers	137863.9	38853.25	349657.8	0	10489305
Revenue, low feedback sellers	116960.9	36551.05	276589.2	33	4737128
Revenue, high feedback sellers	248171.6	72375.46	606723.2	74.64	13891677
Effective percent positive feedback	0.5082	0.5076	0.0583	0	0.8455
Negative feedback share	0.0036	0.0033	0.0036	0	0.1429

Note: N = 61,200.

Table 2: State characteristics

	Mean	Median	SD	Min	Max
Ethnicity dispersion	0.58	0.58	0.16	0.25	0.89
Religiosity index	0.55	0.54	0.11	0.33	0.77
Winner vote % 2016	0.52	0.52	0.13	0.04	0.76
Median income (000)	49.97	48.41	8.13	36.85	68.85
Bachelors share	0.18	0.17	0.03	0.11	0.23
Median age	37.55	37.50	2.32	29.20	42.70
Male share	0.49	0.49	0.01	0.47	0.52
Median home value (000)	197.25	168.80	89.13	95.10	525.40
Urban share	0.73	0.73	0.16	0.33	1.00
Owner-occupied share	0.67	0.68	0.06	0.43	0.75
Observations	51				

Note: Includes all 50 states and the District of Columbia.

Table 3: State pair characteristics

	Mean	Median	SD	Min	Max
Ethnic Difference	0.48	0.48	0.15	0.11	0.89
Religiosity Difference	0.12	0.10	0.09	0.00	0.44
Voting Difference, 2016	0.14	0.12	0.11	0.00	0.71
Difference in …					
Median income (10,000)	0.92	0.76	0.69	0.00	3.20
Bachelors share	0.03	0.03	0.02	0.00	0.13
Median age	2.52	2.00	2.10	0.00	13.50
Male share	0.01	0.01	0.01	0.00	0.05
Median home value (100,000)	0.93	0.69	0.85	0.00	4.30
Urban share	0.18	0.15	0.13	0.00	0.67
Owner-occupied share	0.05	0.04	0.06	0.00	0.32
Dist. between capitals (km)	1941.31	1594.45	1432.79	45.91	8238.13
Observations	2550				

Note: See text for variable definitions

Table 4: The impact of cultural and socioeconomic differences on interstate trade

VARIABLES	(1) log(revenue)	(2) log(revenue)	(3) log(revenue)	(4) log(quantity)	(5) log(quantity)	(6) log(quantity)
Ethnic difference	-0.118***		-0.102***	-0.0929***		-0.0776***
	(0.0197)		(0.0162)	(0.0146)		(0.0123)
Religiosity difference	-0.0188***		-0.0200***	-0.0264***		-0.0262***
	(0.00575)		(0.00546)	(0.00457)		(0.00458)
Voting difference	-0.0407***		-0.0246***	-0.0223***		-0.0122**
	(0.00790)		(0.00586)	(0.00530)		(0.00505)
Median income (000)		0.0112	0.00904		0.00333	0.00326
		(0.00774)	(0.00754)		(0.00543)	(0.00464)
Bachelors share		-0.00332	-0.00123		-0.00712*	-0.00378
		(0.00666)	(0.00613)		(0.00381)	(0.00334)
Median age		0.00346	0.00680		-0.00311	-0.000213
		(0.00492)	(0.00452)		(0.00515)	(0.00413)
Male share		-0.0221**	-0.0215***		-0.00979*	-0.0111**
		(0.00897)	(0.00748)		(0.00575)	(0.00424)
Median home value (000)		-0.0449***	-0.0271**		-0.0207**	-0.0101
		(0.0130)	(0.0121)		(0.00831)	(0.00757)
Urban share		-0.0278***	-0.0147**		-0.0222***	-0.0133***
		(0.00746)	(0.00647)		(0.00494)	(0.00451)
Owner-occupied share		-0.0105	0.00179		-0.0109**	-0.00148
		(0.00865)	(0.00812)		(0.00497)	(0.00469)
Log distance between capitals	-0.139***	-0.140***	-0.127***	-0.114***	-0.120***	-0.107***
	(0.00928)	(0.00959)	(0.00837)	(0.00642)	(0.00808)	(0.00650)
Observations	61,200	61,200	61,200	61,200	61,200	61,200
R-squared (within)	0.359	0.345	0.370	0.478	0.452	0.486

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1 (two-sided test)

Note: In addition to the listed variables, all models include buyer-state × month and seller-state × month fixed effects. The variables median income, bachelors share, median age, male share, median home value, urban share and owner-occupied share all refer to the absolute value of state-level differences. Standard errors are two-way clustered by buyer state and seller state.

Table 5: The impact of taste differences on interstate trade

VARIABLES	(1) log(revenue)	(2) log(revenue)	(3) log(revenue)	(4) log(revenue)
Ethnic difference	-0.102***	-0.0661***	-0.0717***	-0.0649***
	(0.0162)	(0.00902)	(0.0121)	(0.0101)
Religiosity difference	-0.0200***	-0.0236***	-0.0252***	-0.0250***
	(0.00546)	(0.00485)	(0.00481)	(0.00486)
Voting difference	-0.0246***	-0.0112**	-0.0106*	-0.00919
	(0.00586)	(0.00546)	(0.00567)	(0.00575)
Median income (000)	0.00904	0.00938*	0.00925*	0.00935*
	(0.00754)	(0.00471)	(0.00499)	(0.00466)
Bachelors share	-0.00123	-0.00503	-0.00632	-0.00628
	(0.00613)	(0.00456)	(0.00409)	(0.00404)
Median age	0.00680	0.000890	0.00123	0.000348
	(0.00452)	(0.00338)	(0.00348)	(0.00330)
Male share	-0.0215***	-0.0159**	-0.0178***	-0.0163**
	(0.00748)	(0.00611)	(0.00656)	(0.00627)
Median home value (000)	-0.0271**	-0.0197**	-0.0209**	-0.0195**
	(0.0121)	(0.00973)	(0.00891)	(0.00903)
Urban share	-0.0147**	-0.0109**	-0.0112**	-0.0106**
	(0.00647)	(0.00510)	(0.00534)	(0.00524)
Owner-occupied share	0.00179	0.00176	-0.00173	-0.000332
	(0.00812)	(0.00548)	(0.00643)	(0.00593)
Euclidean category distance		-0.267***		-0.141***
(revenue)		(0.0160)		(0.0268)
Cross-product category difference			-0.0784***	-0.0469***
(revenue)			(0.00992)	(0.00770)
Log distance between capitals	-0.127***	-0.123***	-0.121***	-0.121***
	(0.00837)	(0.00767)	(0.00801)	(0.00789)
Observations	61,200	61,200	61,200	61,200
R-squared (within)	0.370	0.415	0.417	0.422

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1 (two-sided test)

Note: In addition to the listed variables, all models include buyer-state × month and seller-state × month fixed effects. The variables median income, bachelors share, median age, male share, median home value, urban share and owner-occupied share all refer to the absolute value of state-level differences. Standard errors are two-way clustered by buyer state and seller state.

Table 6: The moderating role of seller quality in the impact of cultural distance on trade

	(1)	(2a)	(2b)	(3a)	(3b)
	base effect	*base effect, eTRS = 0*	*add'l effect for eTRS = 1*	*base effect, High fdbk = 0*	*add'l effect for High fdbk = 1*
[1] Ethnic difference	-0.0649***	-0.0883***	0.0336*	-0.105***	0.0610***
	(0.0101)	(0.0149)	(0.0179)	(0.0168)	(0.0148)
[2] Religiosity difference	-0.0250***	-0.0259***	0.00478	-0.0225***	-0.00340
	(0.00486)	(0.00446)	(0.00566)	(0.00418)	(0.00511)
[3] Voting difference	-0.00919	-0.0129**	0.00536	-0.0176***	0.0121
	(0.00575)	(0.00490)	(0.00672)	(0.00506)	(0.00744)
Test of sum of [1]-[3] = 0	F = 70.13	F = 74.66	F = 8.16	F = 67.88	F = 18.12
	(p = 0.000)	(p = 0.000)	(p = 0.006)	(p = 0.000)	(p = 0.000)
[4] Median income (000)	0.00935*	0.00739	0.00559	0.0103***	-0.00119
	(0.00466)	(0.00451)	(0.00634)	(0.00274)	(0.00543)
[5] Bachelors share	-0.00628	-0.00523	-0.00608	-0.00887**	0.00234
	(0.00404)	(0.00356)	(0.00486)	(0.00354)	(0.00477)
[6] Median age	0.000348	0.00482	-0.0106**	0.00574	-0.00750
	(0.00330)	(0.00376)	(0.00470)	(0.00361)	(0.00456)
[7] Male share	-0.0163**	-0.0175**	0.00472	-0.0241***	0.0129**
	(0.00627)	(0.00690)	(0.00795)	(0.00718)	(0.00563)
[8] Median home value (000)	-0.0195**	-0.0233**	0.00646	-0.0327***	0.0203*
	(0.00903)	(0.00878)	(0.0124)	(0.00644)	(0.0109)
[9] Urban share	-0.0106**	-0.0130***	0.00597	-0.0179***	0.00893*
	(0.00524)	(0.00463)	(0.00533)	(0.00419)	(0.00525)
[10] Owner-occup. share	-0.000332	-0.00551	0.0120	-0.00629	0.00866
	(0.00593)	(0.00752)	(0.00873)	(0.00791)	(0.00907)
Test of sum of [4]-[10] = 0	F = 15.19	F = 18.97	F = 0.88	F = 29.11	F = 5.39
	(p = 0.000)	(p = 0.000)	(p = 0.354)	(p = 0.000)	(p = 0.024)
Euclidean categ dist (revenue)	-0.141***	-0.128***	-0.0396	-0.0594	-0.124***
	(0.0268)	(0.0360)	(0.0582)	(0.0370)	(0.0309)
Cross-product categ diff (revenue)	-0.0469***	-0.0202***	-0.0361**	-0.00574	-0.0539***
	(0.00770)	(0.00420)	(0.0167)	(0.00795)	(0.0152)
Log distance between capitals	-0.121***	-0.129***	0.0165**	-0.143***	0.0290***
	(0.00789)	(0.00879)	(0.00732)	(0.00853)	(0.00667)
Observations	61,200	122,400		122,400	
R-squared (within)	0.422	0.294		0.313	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1 (two-sided test)

Note: In addition to the listed variables, all models include buyer-state × month and seller-state × month fixed effects. The variables median income, bachelors share, median age, male share, median home value, urban share and owner-occupied share all refer to the absolute value of state-level differences. Standard errors are two-way clustered by buyer state and seller state.

Table 7: The impact of cultural distance on customer satisfaction

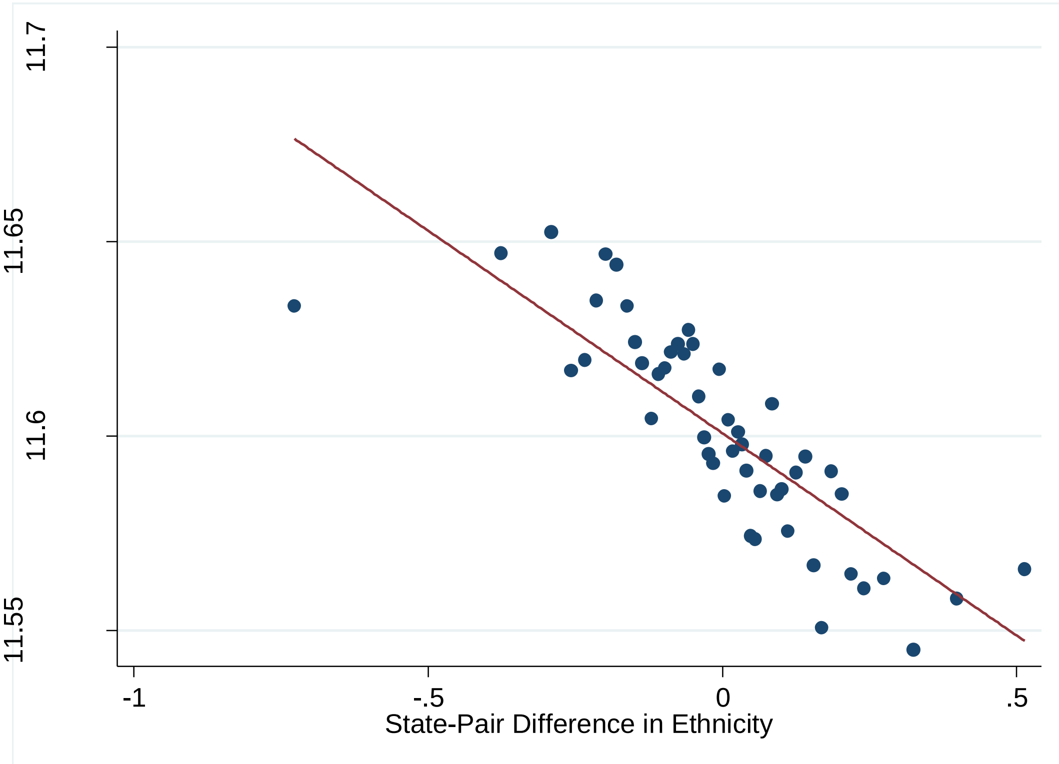
VARIABLES	(1) EPP	(2) EPP	(3) Negative feedback	(4) Negative feedback
Ethnic Difference	-0.00168	-0.00223	5.38e-06	-3.54e-05
	(0.00149)	(0.00167)	(0.000109)	(0.000108)
Religiosity Difference	0.000298	-4.00e-05	-1.07e-05	-6.76e-07
	(0.000317)	(0.000313)	(1.39e-05)	(1.57e-05)
Voting Difference	-0.000373	0.000111	0.000144***	0.000121***
	(0.000771)	(0.000815)	(4.58e-05)	(3.92e-05)
Median income (000)	0.000160	0.000157	3.28e-05	3.27e-05
	(0.000534)	(0.000560)	(4.60e-05)	(4.53e-05)
Bachelors share	0.000114	4.83e-05	-9.21e-06	-7.76e-07
	(0.000640)	(0.000654)	(1.36e-05)	(1.21e-05)
Median age	-5.65e-06	-0.000215	3.09e-05	3.99e-05
	(0.000646)	(0.000639)	(3.43e-05)	(3.70e-05)
Male share	0.000689	0.000919	3.74e-05	3.16e-05
	(0.000610)	(0.000590)	(4.00e-05)	(3.98e-05)
Median home value (000)	-0.000393	-0.000121	-0.000112**	-0.000122**
	(0.000884)	(0.000879)	(5.13e-05)	(5.03e-05)
Urban share	0.00101	0.00111*	-1.35e-05	-1.91e-05
	(0.000640)	(0.000645)	(2.49e-05)	(2.48e-05)
Owner-occupied share	-0.000250	-0.000269	-6.49e-05	-5.77e-05
	(0.000666)	(0.000628)	(5.44e-05)	(5.66e-05)
Log distance between capitals	-0.00520***	-0.00508***	0.000150***	0.000139***
	(0.000860)	(0.000843)	(3.09e-05)	(2.70e-05)
Euclidean category distance	0.00883**		6.92e-05	
(revenue)	(0.00383)		(0.000341)	
Cross-product category difference	0.000157		-0.000148	
(revenue)	(0.000985)		(0.000152)	
Euclidean category distance		0.0168***		-0.000102
(quantity)		(0.00408)		(0.000212)
Cross-product category difference		-0.0124***		8.90e-05
(quantity)		(0.00404)		(0.000295)
Observations	61,200	61,200	61,199	61,199
R-squared (within)	0.011	0.013	0.002	0.002

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1 (two-sided test)

Note: In addition to the listed variables, all models include buyer-state × month and seller-state × month fixed effects. The variables median income, bachelors share, median age, male share, median home value, urban share and owner-occupied share all refer to the absolute value of state-level differences. Standard errors are two-way clustered by buyer state and seller state.

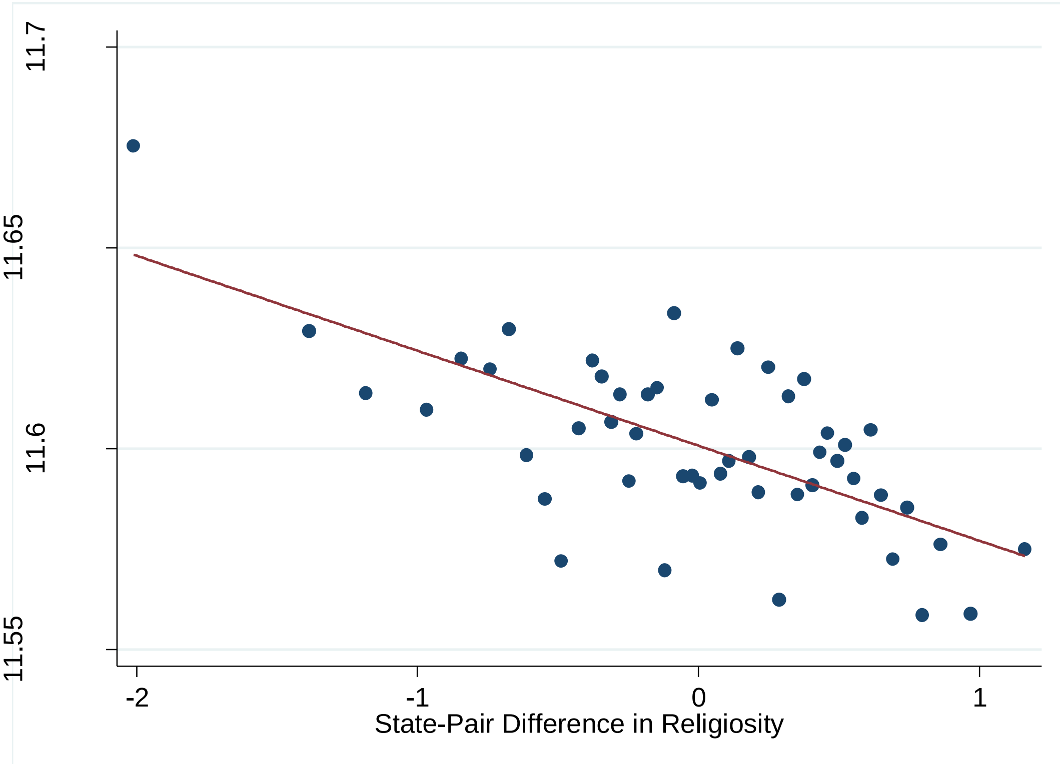
APPENDIX

Figure A1: Relationship between ethnic differences and interstate trade



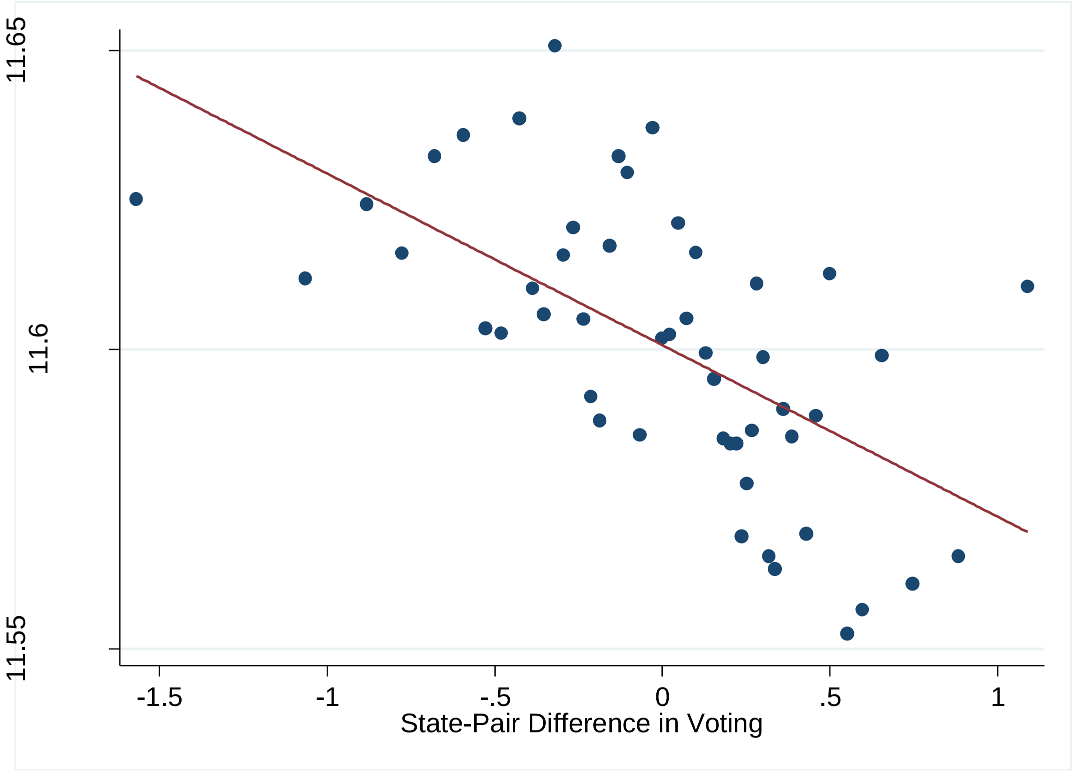
Note: The figure shows a binned scatter plot to illustrate the relationship between state-pair differences in ethnicity and interstate trade. We use 50 bins, and residualize the data to account for all other variables included in Table 4, column 3.

Figure A2: Relationship between differences in religiosity interstate trade



Note: The figure shows a binned scatter plot to illustrate the relationship between state-pair differences in religiosity and interstate trade. We use 50 bins, and residualize the data to account for all other variables included in Table 4, column 3.

Figure A3: Relationship between differences in voting and interstate trade



Note: The figure shows a binned scatter plot to illustrate the relationship between state-pair differences in voting in the 2016 presidential election and interstate trade. We use 50 bins, and residualize the data to account for all other variables included in Table 4, column 3.

Table A1: Quantity-focused taste and trade models

VARIABLES	(1) log(quantity)	(2) log(quantity)	(3) log(quantity)	(4) log(quantity)
Ethnic difference	-0.0776***	-0.0350***	-0.0501***	-0.0349***
	(0.0123)	(0.00686)	(0.0102)	(0.00673)
Religiosity difference	-0.0262***	-0.0228***	-0.0246***	-0.0228***
	(0.00458)	(0.00377)	(0.00397)	(0.00373)
Voting difference	-0.0122**	-0.0108**	-0.0107**	-0.0109**
	(0.00505)	(0.00434)	(0.00469)	(0.00442)
Median income (000)	0.00326	0.00264	0.00251	0.00266
	(0.00464)	(0.00346)	(0.00390)	(0.00341)
Bachelors share	-0.00378	-0.00652***	-0.00593**	-0.00650***
	(0.00334)	(0.00242)	(0.00264)	(0.00242)
Median age	-0.000213	-5.43e-05	-7.39e-05	-5.59e-05
	(0.00413)	(0.00328)	(0.00328)	(0.00329)
Male share	-0.0111**	-0.0112***	-0.0109***	-0.0112***
	(0.00424)	(0.00382)	(0.00399)	(0.00383)
Median home value (000)	-0.0101	-0.00801	-0.00788	-0.00805
	(0.00757)	(0.00626)	(0.00640)	(0.00614)
Urban share	-0.0133***	-0.0123***	-0.0126***	-0.0123***
	(0.00451)	(0.00334)	(0.00376)	(0.00334)
Owner-occupied share	-0.00148	-0.00555*	-0.00565	-0.00547*
	(0.00469)	(0.00320)	(0.00360)	(0.00314)
Euclidean category distance		-0.141***		-0.147***
(quantity)		(0.0232)		(0.0320)
Cross-product category distance			-0.105**	0.00654
(quantity)				
			(0.0398)	(0.0396)
Log distance between capitals	-0.107***	-0.107***	-0.107***	-0.107***
	(0.00650)	(0.00610)	(0.00632)	(0.00609)
Observations	61,200	61,200	61,200	61,200
R-squared (within)	0.486	0.532	0.518	0.532

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1 (two-sided test)

Note: In addition to the listed variables, all models include buyer-state × month and seller-state × month fixed effects. The variables median income, bachelors share, median age, male share, median home value, urban share and owner-occupied share all refer to the absolute value of state-level differences. Standard errors are two-way clustered by buyer state and seller state.

Table A2: Quantity-focused trust and trade models

	(1)	(2a)	(2b)	(3a)	(3b)
	base effect	*base effect, eTRS = 0*	*add'l effect for eTRS = 1*	*base effect, High fdbk = 0*	*add'l effect for High fdbk = 1*
[1] Ethnic difference	-0.0349***	-0.0590***	0.0347	-0.0911***	0.0733***
	(0.00673)	(0.0136)	(0.0212)	(0.0127)	(0.0139)
[2] Religiosity difference	-0.0228***	-0.0259***	0.00792**	-0.0222***	0.000274
	(0.00373)	(0.00365)	(0.00374)	(0.00362)	(0.00404)
[3] Voting difference	-0.0109**	-0.0124***	0.00365	-0.0143***	0.00437
	(0.00442)	(0.00424)	(0.00623)	(0.00344)	(0.00478)
Test sum of [1]-[3] = 0	F = 85.68	F = 51.9	F = 5.67	F = 97.78	F = 30.89
	(p = 0.000)	(p = 0.000)	(p = 0.021)	(p = 0.000)	(p = 0.000)
[4] Median income (000)	0.00375	0.00252	0.00323	0.00496*	-0.00196
	(0.00507)	(0.00401)	(0.00502)	(0.00253)	(0.00344)
[5] Bachelors share	-0.226**	-0.00467*	-0.00525	-0.00793***	0.00130
	(0.109)	(0.00271)	(0.00376)	(0.00271)	(0.00334)
[6] Median age	-0.000354	0.00143	-0.00381	0.00273	-0.00325
	(0.00149)	(0.00387)	(0.00269)	(0.00174)	(0.00432)
[7] Male share	-1.377**	-0.00981*	-0.00385	-0.0174***	0.00989**
	(0.524)	(0.00501)	(0.00556)	(0.00450)	(0.00438)
[8] Median home value (000)	-0.0115	-0.0122**	0.00430	-0.0220***	0.0181**
	(0.00711)	(0.00559)	(0.00990)	(0.00464)	(0.00734)
[9] Urban share	-0.0745***	-0.0150***	0.00622	-0.0174***	0.00617
	(0.0219)	(0.00341)	(0.00407)	(0.00266)	(0.00379)
[10] Owner-occupied share	-0.0502	-0.00553	0.00347	-0.00352	-0.00252
	(0.0785)	(0.00508)	(0.00655)	(0.00561)	(0.00566)
Test sum of [4]-[10] = 0	F = 31.13	F = 25.71	F = 0.20	F = 31.72	F = 6.14
	(p = 0.000)	(p = 0.000)	(p = 0.660)	(p = 0.000)	(p = 0.017)
Euclidean categ dist (quantity)	-0.147***	-0.119***	-0.0448	-0.0553**	-0.114***
	(0.0320)	(0.0239)	(0.0469)	(0.0248)	(0.0342)
Cross-product categ diff (quantity)	0.00654	0.0303	-0.0387	0.0144	-0.0106
	(0.0396)	(0.0369)	(0.0343)	(0.0213)	(0.0339)
Log distance between capitals	-0.107***	-0.116***	0.0190***	-0.128***	0.0250***
	(0.00609)	(0.00680)	(0.00470)	(0.00572)	(0.00555)
Observations	61,200	122,400		122,400	
R-squared (within)	0.532	0.393		0.487	

Note: In addition to the listed variables, all models include buyer-state × month and seller-state × month fixed effects separately for each *eTRS* value. The variables median income, bachelors share, median age, male share, median home value, urban share and owner-occupied share all refer to the absolute value of state-level differences. Standard errors are two-way clustered by buyer state and seller state.