INTERNATIONAL TRADE AND SOCIAL CONNECTEDNESS*

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Abstract

We use de-identified data from Facebook to construct a new and publicly available measure of the pairwise social connectedness between 170 countries and 332 European regions. We find that two countries trade more when they are more socially connected, especially for goods where information frictions may be large. The social connections that predict trade in specific products are those between the regions where the product is produced in the exporting country and the regions where it is used in the importing country. Once we control for social connectedness, the estimated effects of geographic distance and country borders on trade decline substantially.

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The propensity for residents of different countries to be connected to one another varies enormously. For example, a U.S.-based Facebook user is 65% more likely to be friends with a given Facebook user living in Germany than with a given Facebook user living in France. Such differences in bilateral social connectedness play an important role in many narratives of economic and political interactions between countries. For example, beginning with Tinbergen (1962), researchers have explored the determinants of international trade using gravity models that relate trade between countries to various measures of the relationship between those countries.[1] These models have had substantial empirical success, but their economic underpinnings—and especially the mechanisms behind the large estimated negative effect of physical distance on trade—have remained elusive. One prominent explanation is that geographic closeness proxies for social connections between individuals, which can help facilitate trade. While such a mechanism is intuitively appealing, the absence of comprehensive data on social connections across regions and countries has limited researchers' ability to provide evidence in favor of this interpretation.

In this paper, we introduce a new measure of the pairwise social connectedness between 170 countries and 332 European regions, and show that much of the variation in global trade can indeed be explained by patterns of social connectedness. We also find support for mechanisms proposed by theoretical models in which social connectedness facilitate trade by reducing information frictions.[2] By exploiting the granular nature of our social connectedness measure and detailed data on the geography of production, we are able to further understand the impact of social connectedness on trade flows. Specifically, we show that it is the social connections between the regions where a good is produced in the exporting country and those regions where it is used in the importing country that predict trade in that good. Once we control for social connectedness, the estimated effects of geographic distance and country borders on trade decline substantially.

Our measure of social connectedness is based on a de-identified snapshot of all friendship links on Facebook, the world's largest online networking site with more than 2.7 billion active users around the globe. Our *Social Connectedness Index* between pairs of regions corresponds to the relative probability of a friendship link between Facebook users in the two regions. We construct this pairwise measure of social connectedness for 170 countries and 332 European regions. To facilitate further research on the relationship between social connectedness and trade flows, we have made the *Social Connectedness Index* publicly available to other researchers.[3]

When relating the *Social Connectedness Index* to trade flows, we do not interpret our findings as evidence that Facebook links directly cause or facilitate trade. Instead, we interpret our measure of social connectedness as providing a high-quality proxy for existing trade-facilitating relationships across countries and regions. The ability of our data to capture these relationships at a geographically disaggregated level is the result of Facebook's scale, the relative representativeness of its user body, and the fact that

[1] Prominent contributions that have explored the relationship between geography and trade include Leamer and Levinsohn (1995), Trefler (1995), Obstfeld and Rogoff (2000), Eaton and Kortum (2002), and Hortaçsu et al. (2009).

[2] Papers which study the role of information frictions in international trade include, Jensen (2007); Aker (2010); Allen (2014); Chaney (2014); Simonovska and Waugh (2014); Startz (2016); Steinwender (2018)

[3] This new and comprehensive measure of international social connectedness can be downloaded at `https://data.humdata.org/dataset/social-connectedness-index`. See Bailey et al. (2018a, 2020a) for a description of a related data set measuring the social connectedness between U.S. counties, and between zip codes in the New York metro area. See Bali et al. (2018), Hirshleifer et al. (2019), Rehbein et al. (2020), Kuchler et al. (2020a,b),Bailey et al. (2020b), and Wilson (2019) for recent uses of the U.S. Social Connectedness Index in economics and finance research.

people primarily use Facebook to interact with real-world friends and acquaintances. Throughout the paper, we present a number of results that mitigate concerns that our findings are the result of omitted country-level variables or reverse causality whereby trade flows lead to more underlying friendships.

We first describe the rich patterns of social connectedness observed in our data. About half the variation in social connectedness between countries is explained by geographic distance. Quantitatively, a 10% increase in the distance between two countries is associated with a 10%–15% decline in their social connectedness. Migration patterns and colonial history further influence the probability of present-day friendship links across country pairs. We also find stronger social connections between countries that share a common language, as well as between countries that are similar in terms of economic development, religious beliefs, and the genetic make-up of their populations. Within Europe, common language and common history shape the social connectedness between regions over and above distance and common nationality. Beyond these systematic patterns, our measure of social connectedness is also affected by idiosyncratic factors that are specific to particular country and region pairs.

Next, we document that patterns of social connectedness explain a substantial part of the variation in international trade flows. When we introduce social connectedness into a standard gravity model of country-level goods trade, we find that social connectedness and geographic distance explain similar shares of the cross-sectional variation in trade flows. The elasticity of trade in goods with respect to social connectedness is 0.28 in specifications that also control for geographic distance. This implies that, all else equal, trade between the U.S. and Germany should be 18% higher than trade between the U.S. and France, since the U.S. is 65% more connected to Germany than it is to France. Controlling for social connectedness reduces the distance elasticity of trade from about -1 to roughly -0.70. This is a substantial decline that does not occur when controlling for other gravity variables such as common language or common colonial origins. Social connectedness as measured by today's Facebook links strongly explains trade flows at least since the 1980s, demonstrating that the underlying trade-facilitating relationships across countries are very stable over time. The combined evidence suggests that social connectedness is an important determinant of trade flows, and highlights that the relationship between geographic distance and trade in the prior literature might partially capture this role of social connectedness.

We then explore possible explanations for the observed relationship between trade flows and social connectedness. In particular, the literature has proposed that social links can facilitate trade by alleviating a number of informal trade barriers, including contract enforcement frictions and search costs due to information frictions (see Chaney, 2016, for a review). We provide evidence suggesting that social links as measured through the *Social Connectedness Index* help alleviate information frictions while they do not appear to significantly mitigate contract enforcement frictions.

We first study how the elasticity of trade with respect to social connectedness varies for trade in different products. In particular, Rauch (1999) and Rauch and Trindade (2002) suggest that information frictions are largest for products that are not traded on organized exchanges. Consistent with the idea that social connections can help to mitigate such information frictions, we show that the elasticity of trade to social connectedness is particularly large for these non-exchange-traded goods. To understand whether social connectedness can mitigate contract enforcement frictions, we also study how the elasticity varies with measures of the rule of law in the importing and exporting countries. This analysis is motivated by a literature that shows that weak rule of law reduces trade due to difficulties with the enforcement of contracts (e.g., Anderson and Marcouiller, 2002). In these regressions, we find little variation in the elasticity across countries with different levels of rule of law, suggesting that the primary channel behind the observed aggregate relationships is the reduction of information frictions.

After documenting how social connectedness relates to trade at the country level, we use our granular measure of social connectedness across sub-national European regions to further understand the mechanism behind the observed relationships. Our results in that section provide new evidence on the interaction of trade flows, the spatial distribution of production, and the structure of social networks. Our findings also help us rule out country-level omitted variables or reverse causality as alternative interpretations of the observed aggregate relationship between social connectedness and trade.

Our approach builds on a literature that documents that firms and individuals working at those firms are central to facilitating international goods trade.[4]Based on this insight, we construct *product-specific* measures of the social connectedness between countries, which overweight the connectedness between those regions where the goods are produced in the exporting country and those regions where the goods are used in the importing country. This measure contrasts with our baseline measure of social connectedness between two countries, which corresponds to the population-weighted average connectedness between all regions in the countries. As an example, more than 80% of Italian exports of non-metallic mineral products to Greece are used as inputs in the Greek construction sector. Our proposed measure of social connectedness relevant for exporting non-metallic mineral products from Italy to Greece thus overweights the observed connectedness between the regions that produce non-metallic mineral products in Italy (primarily the Piedmont region around Torino) and the regions with significant construction employment in Greece (e.g., the Attica region around Athens).

We then regress product-level trade between countries on both measures of social connectedness. When controlling for the product-specific measure of social connectedness, the population-weighted measure has no further predictive power for trade at the product-level. This remains true after controlling for product-specific measures of distance. This evidence suggests that it really is the social connectedness between the regions where a good is produced and the regions where it is used that matters for trade in that good. We also find that the elasticity of trade to the product-specific measures of social connectedness is unaffected by the inclusion of country pair fixed effects, which absorb all country-level determinants of trade. This finding dramatically reduces the scope for omitted variables such as common preferences to explain the observed relationships between social connectedness and trade.

Our analysis of the effects on trade of product-specific social connectedness between countries also allows us to rule out the presence of a quantitatively large reverse causality from trade to our measure of connectedness. If trade did in fact cause substantial social connections, the various product-specific measures of social connectedness between two countries should be systematically larger than these countries' measures of population-weighted social connectedness. For instance, in the example above, we would expect the Piedmont region in Italy and the Attica region in Greece to be disproportionately more connected than a random pair of regions in the two countries, as a result of the connections formed

[4]Papers that study the importance of firms in trade include Melitz (2003), Bernard et al. (2003), Bernard et al. (2007), Chaney (2008), Helpman et al. (2008), Melitz and Ottaviano (2008), Chaney (2018), and Bernard et al. (2012).

from trading non-metallic mineral products. In contrast with this prediction, we find that the regions that are most important for the trade in a given product are equally likely to be more or less connected than two random regions across a country pair.

In the final part of the paper, we study the relationship between regional social connectedness and sub-national goods trade. We use rail-freight flows between regions in the European Union as our measure of trade flows. This analysis allows us to examine the determinants of the border effect, the empirical regularity that, conditional on the distance between two regions, trade is much larger between regions of same country (see McCallum, 1995; Anderson and Van Wincoop, 2003; Chen, 2004). Consistent with existing estimates of the border effect, we find that, all else equal, trade within countries is seven to nine times as large as trade between countries. This is true despite the fact that the European Union is a common market with few formal barriers to cross-country trade. When we control for the social connections between regions, the estimated border effect drops by between 65% and 80% across various specifications. This suggests that much of the effect of borders on trade may be the result of the fact that social connections fall at borders.

The rest of the paper is organized as follows. Section 1 presents our new measure of international social connectedness and explores its determinants. Section 2 describes the relationship between international trade flows and social connectedness, focusing on heterogeneities across products and countries. In Section 3, we present results using our product-specific measures of social connectedness and explore patterns in regional trade within Europe.

1 Measuring International Social Connectedness

We construct our measure of the social connectedness between countries and European regions using de-identified administrative data from Facebook, a global online social networking service. Facebook was created in 2004, and, by the second quarter of of 2020, had 2.7 billion monthly active users globally. Of these monthly active users, 256 million were based in the U.S. and Canada, 410 million in Europe, 1.14 billion in the Asia-Pacific region, and 892 million in the rest of the world. With the exception of a few countries where social media services including Facebook are banned—most notably China, Iran, and North Korea—Facebook has a non-trivial footprint in essentially all countries around the world.

We work with a de-identified snapshot of all active Facebook users from August 2020. For these users, we observe their country of location, as well as the set of other Facebook users that they are connected to. For users in Europe, we also observe their region of location at the NUTS2 (Nomenclature of Territorial Units for Statistics level 2 regions) level, similar to Bailey et al. (2020c). These NUTS2 regions include between 800,000 and 3,000,000 individuals, and are defined for European Union members, European Union candidates, and European Free Trade Association members. They are generally based on existing subnational administrative borders. For example, in Italy the NUTS2 geographies correspond to the 21 "regions", while in the Netherlands they correspond to the 12 "provinces"; smaller countries in Europe, such as Latvia and Malta, are represented by a single NUTS2 region. Location in a country or region is assigned based on users' information and activity on Facebook, including the stated city on their Facebook profile, and device and connection information.

To compare the intensity of social connectedness between locations with varying populations and varying Facebook usage rates, we construct our *Social Connectedness Index*, $SCI_{i,j}$, as the total number of connections between individuals in location i and individuals in location j, divided by the product of the number of Facebook users in those locations, as in Equation 1:

$$SCI_{i,j} = \frac{FB\_Connections_{i,j}}{FB\_Users_i \times FB\_Users_j}. \tag{1}$$

For both countries and regions, we rescale this number to have a minimum value of 1, and a maximum value of 1,000,000. The *Social Connectedness Index* therefore measures the *relative* probability of a Facebook friendship link between a given Facebook user in location i and a given user in location j. Overall, we will work with information on the pairwise social connectedness between 170 countries, for a total of $170 \times 169 = 28,730$ country-pair combinations. At the NUTS2 level, we observe the social connectedness between $332 \times 331 = 109,892$ pairs of European regions.[5]

Interpreting the Social Connectedness Index. Two important questions arise when interpreting $SCI_{i,j}$ as a proxy for potentially trade-facilitating relations between countries or regions: whether Facebook friendships correspond to real-world friendship links of Facebook users, and whether Facebook users are representative of the countries' or regions' populations.

On the first issue, we believe that Facebook friendships provide a reasonable proxy for real world friendship networks. For the United States, Duggan et al. (2015) have shown that Facebook friendship patterns correspond closely to real-world friendship networks. While similar studies do not exist for most other countries, we believe that there are a number of reasons to think that we are also capturing good representations of real-world social networks of Facebook users outside of the United States. For example, establishing a connection on Facebook requires the consent of both individuals, and there is an upper limit of 5,000 on the number of connections a person can have. As a result, networks formed on Facebook will more closely resemble real-world social networks than those on other online platforms, such as Twitter, where uni-directional links to non-acquaintances, such as celebrities, are common. Consistent with this conclusion, our prior work with micro-data from Facebook has found that many economic decisions, such as whether to buy a house or which phone to purchase, are influenced by related decisions of a person's Facebook friends (Bailey et al., 2018b, 2019a,b).

On the second issue, it is likely that the representativeness of Facebook users will differ across locations. While Duggan et al. (2016) have shown that U.S. Facebook users are quite representative of the U.S. population, this is unlikely to be the case everywhere. For example, in countries with relatively low internet penetrations, those individuals with access to the internet are likely to be a non-representative subset of the overall populations. To the extent that having internet access and having friends abroad are positively correlated, our measure would then overstate the international linkages of the average

[5]The publicly available *Social Connectedness Index* data does not include information for a number of countries, such as Afghanistan, China, Cuba, Eritrea, Iran, Iraq, Israel, North Korea, Russia, Somalia, Sudan, Syria, Tajikistan, Turkmenistan, Venezuela, Western Sahara, and Yemen. In addition, we are missing gravity variables for a number of countries that are included in the SCI data (e.g., Montenegro, Serbia, and Kosovo).

resident in countries with low internet usage.[6] In our analysis, we account for such heterogeneities in the average connectedness of each location by including fixed effects for locations i and j in all specifications. This approach allows us to explore connectedness between locations i and j, holding fixed the average propensity in each location of having Facebook friends in different places.

In the end, while no measure of social connectedness is perfect, we believe that our *Social Connectedness Index*, which is based on hundreds of billions of Facebook friendship links from 2.7 billion Facebook users, provides a valuable large-scale measure of the geographic distribution of social networks. Indeed, it is hard to imagine an alternative measure that would allow us to measure social connections at this scale and scope. We hope that the easy accessibility of our *Social Connectedness Index* will facilitate more research on the role of social connectedness in economics and across the social sciences.

Determinants of Social Connectedness. We next explore a number of factors that help explain the observed patterns of social connectedness across locations. We summarize our central findings in the main body of the paper and present a more extensive analysis in Appendix A.

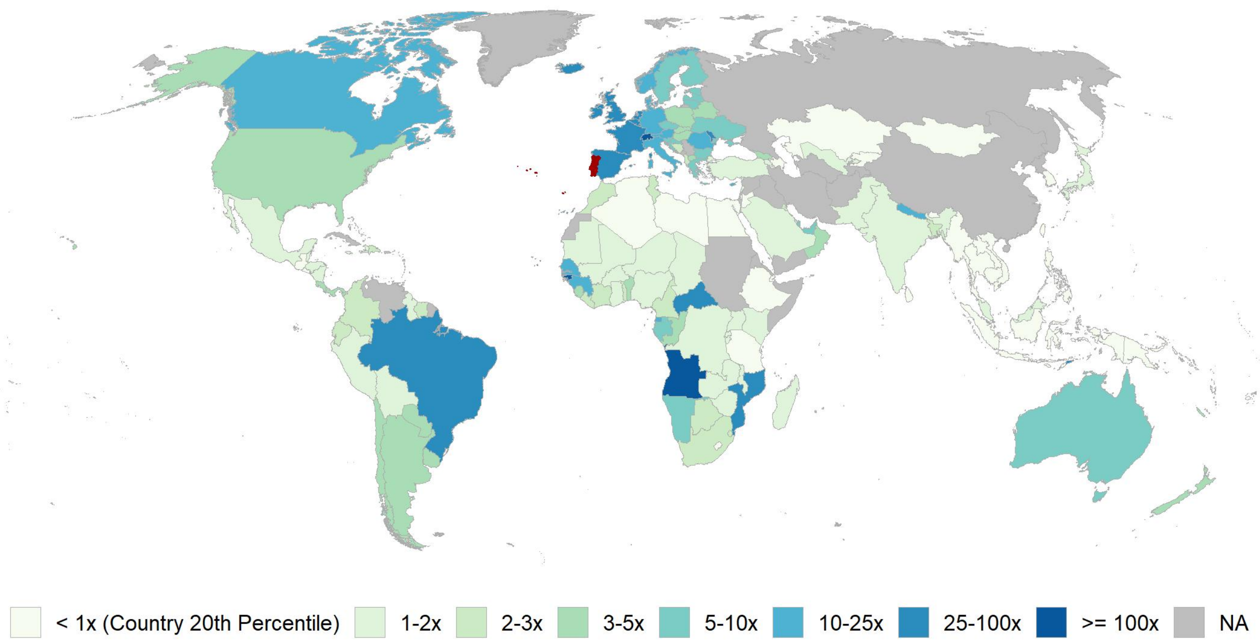
We begin by exploring a few case studies that highlight how social connectedness varies across specific countries and regions. Panel A of Figure 1 shows the social connectedness of Portugal to other countries around the world. Darker colors correspond to higher connectedness. Portugal has the strongest links to geographically close countries in Western Europe. Portugal's international connections also highlight the role of colonial history and language in shaping present-day social connectedness. The country is strongly connected to its former (Portuguese-speaking) colonies Brazil, Angola, Guinea-Bissau, and Mozambique. Within Europe, Portugal is most strongly connected to Luxembourg. These connections, which are stronger than the connections to Portugal's neighbor Spain, are likely related to the fact that 15%–20% of Luxembourg's population is of Portuguese origin, following large-scale migration from Portugal to Luxembourg as part of a guest worker program in the 1960s. This finding suggests that past migration movements continue to influence social connections today.

In Appendix A, we explore the determinants of international social connectedness more systematically. We find that a 10% increase in the distance between two countries is associated with a 10%–15% decline in their social connectedness. Geographic distance explains about 50% of the variation in social connectedness that remains after accounting for country fixed effects. Consistent with our findings for Portugal, international migration patterns and colonial history strongly influence the probability of present-day friendship links across all country pairs. We also find more social connections between countries sharing a common language, as well as between countries that are similar in terms of economic development, religious beliefs, and the genetic make-up of their populations. However, while about 70% of the variation in social connectedness across country pairs can be explained by distance, language, and other systematic factors, our *Social Connectedness Index* also captures a wide variety of idiosyncratic forces that can shape the social connections between two countries. For example, citizens of Denmark and Australia are 75% more connected than would be predicted purely by the observable factors described above. These strong social connections between Denmark and Australia are likely the

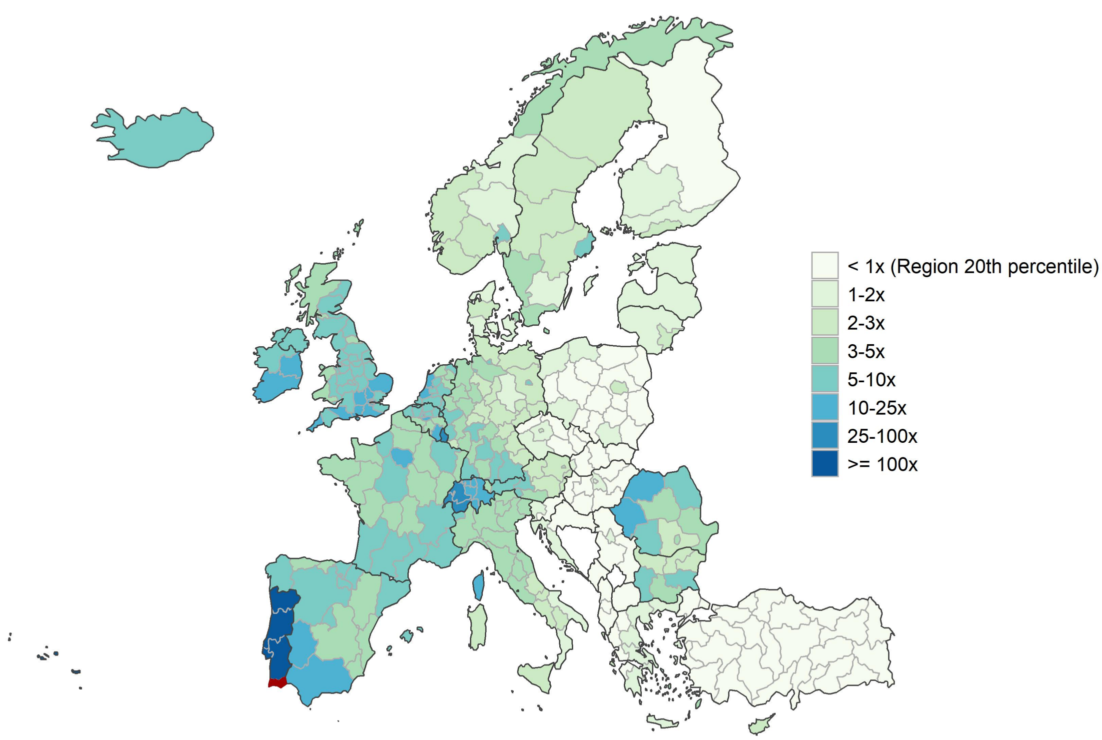
[6] Differential online access is less of an issue across our European regions. Indeed, statistics from Eurostat show that in 2019, 90% of households in the European Union had access to the internet. However, Facebook usage rates conditional on internet access can still vary in systematic ways across these regions. As a result, one might worry that Facebook users in regions with lower Facebook penetrations are connected to other regions at rates that are not representative of the full populations.

Figure 1: Social Connectedness of Portugal and Algarve Region

(A) Social Connectedness of Portugal to other countries



(B) Social Connectedness of the Algarve Region in Portugal to European regions



Note: Figure shows a heat map of the social connectedness of Portugal to other countries (Panel A) and of the Algarve region in Portugal to other European regions (Panel B). For each location, the colors highlight connections of the focal location, given in red. The lightest color corresponds to the 20th percentile of the connectedness across country pairs that include Portugal in Panel A and region pairs that include Algarve in Panel B; darker colors correspond to closer connections.

result of the 2004 marriage of the Danish Crown Prince Frederik to Australian-born Mary Donaldson. This marriage led to heightened mutual interest between Danish and Australian citizens, and has substantially increased tourism between the two countries.[7] Examples such as this highlight the power of our approach to measuring social connectedness over and above competing approaches that proxy for social connectedness using a variety of other gravity variables.

Panel B of Figure 1 shows the connectedness of the Algarve region in southern Portugal to other regions within Europe. The strongest social links are to other regions in Portugal. Indeed, the Algarve region is much more strongly connected to the Norte region in the very north of Portugal than it is to the Andalusia region, its neighbor just across the border in Spain. The Algarve's connections to other European regions show some of the same patterns seen for Portugal as a whole, such as the strong connections to Luxembourg. However, additional nuances are visible at the regional level. At the country level, Portugal showed strong connections to France. When exploring regional social connectedness, we find that connections from Algarve are particularly strong to Southern France and Corsica, which has a substantial number of Portuguese immigrants. The Algarve also has strong connections to much of Western Europe, from where it attracts many tourists each year.

The forces highlighted in Panel B of Figure 1 also show up in more systematic analyses. Indeed, Bailey et al. (2020c) show that social connectedness within Europe varies with patterns of migration, political borders, geographic distance, language, and other demographics. The elasticity of social connectedness with respect to distance across European regions is -1.3, similar to comparable elasticities across countries. Social connectedness drops off sharply at country borders, even after controlling for distance: depending on the country, the probability of friendship between two individuals living in the same country is five to eighteen times as large as the probability of friendship across two individuals living in different countries. In addition, regions that are more similar along demographic measures such as language, religion, education, and age are more socially connected. Interestingly, the relationship between political borders and connectedness can persist many decades after boundaries change. For example, Bailey et al. (2020c) finds higher social connectedness across regions that were originally part of the Austro-Hungarian empire, even after controlling for a host of other determinants of present-day social connectedness.

2 Country-level Trade and Social Connectedness

We now turn to understanding the relationship between social connectedness and trade at the country level. We first document that trade flows are increasing in social connectedness and show that these effects are larger for goods where information frictions may be important, suggesting that social connections may facilitate trade by reducing these frictions.

We measure country-level trade flows using bilateral goods trade data from CEPII (Gaulier and Zignago, 2010). In our baseline analysis, we explore data from 2017, though our results are robust to using trade data from earlier or later years. The raw trade data is disaggregated at the 6-digit HS96 code level, and contains information on 4,914 product categories. For our first analysis, we aggregate

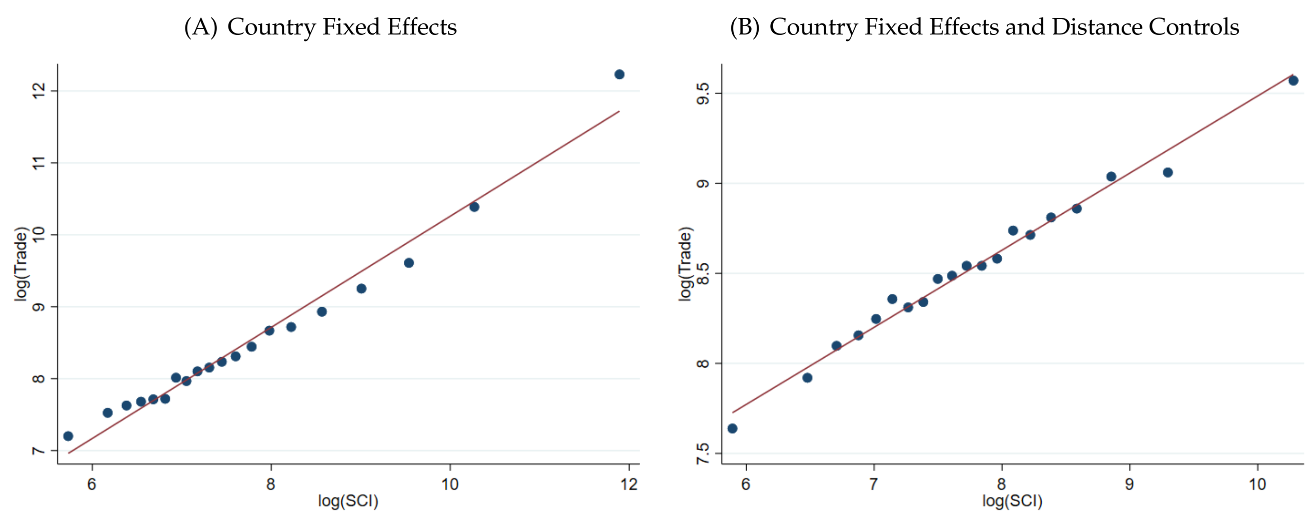
[7] The Australian Department of Foreign Affairs and Trade notes on its country brief on Denmark that "Australia's profile in Denmark, and vice-versa, was boosted by the marriage in May 2004 of Australian-born Mary Donaldson to Denmark's Crown Prince Frederik" and the press reported an increase of 30% in tourism from Australia to Denmark in 2004.

the product-level trade data into bilateral trade flows between country pairs. When merged with social connectedness and gravity data, we have information on 27,060 country pairs.[8] To understand the relationship between social connectedness and trade flows, we follow the literature to estimate the following gravity regression:

$$X_{i,j} = \exp\left[\beta_1 \log(SCI_{i,j}) + \beta_2 \log(Distance_{i,j}) + \beta_3 G_{i,j} + \delta_i + \delta_j\right] \cdot \epsilon_{i,j}, \tag{2}$$

where $X_{i,j}$ denotes the total value of exports from country i to country j, $G_{i,j}$ captures country pair characteristics, δ_i and δ_j are exporter and importer fixed effects, and $\epsilon_{i,j}$ is an error term. The importer and exporter fixed effects control for country-level characteristics such as population, GDP, and average tariffs, all of which affect the overall level of trade; they also control for country-specific differences in the use of Facebook that might affect our measure of social connectedness. We follow a large literature and control for geographic distance between countries with the log of distance, but will show robustness of all results to including non-parametric distance controls. The main variable of interest, $SCI_{i,j}$, is also included in logs. This choice of functional form is based on the evidence from the binscatter plots in Figure 2, which show that the relationship between exports and social connectedness is approximately log-linear. We estimate regression 2 using Poisson Pseudo Maximum Likelihood (PPML) to account for zero bilateral trade between many country pairs (see the discussion in Santos Silva and Tenreyro, 2006).[9]

Figure 2: Aggregate Goods Trade vs. Social Connectedness



Note: Figures show binscatter plots of aggregate bilateral trade and social connectedness. Panel A regresses log(Exports) on log(SCI) without controlling for distance, while Panel B includes log(Distance) as a control. Both panels control for exporter and importer fixed effects. Here, we focus on the intensive margin of trade, which reduces our sample to 18,393 observations.

The results from estimating regression 2 are presented in Table 1. Column 1 shows results from a specification with only importer and exporter fixed effects. The R^2 highlights that 83.7% of the variation

[8]This corresponds to pairwise trade data from 165 countries. Relative to the analysis in Section A, we lose Botswana, Lesotho, Luxembourg, Namibia, and Swaziland, for which we have data on social connectedness, but no data on trade.

[9]Our estimation uses the algorithm in Correia et al. (2019a,b). In the appendix, we present estimates of regression 2 in logs while dropping observations with zero trade flows (i.e., we focus on exploring the effect of social connectedness on the intensive margin of trade). All findings are robust to this deviation from the PPML estimation approach.

in bilateral trade flows is explained by these fixed effects alone. This finding is unsurprising, since larger and richer countries will trade substantially more on average. Column 2 introduces controls for the social connectedness between each country pair. The elasticity of trade with respect to social connectedness is an economically significant 0.65, suggesting that a 1% increase in social connectedness is associated with a 0.65% increase in bilateral trade. Variation in social connectedness accounts for a substantial share of the cross-sectional variation in trade flows: over half of the variation in bilateral trade flows that is not explained by the country fixed effects is explained by social connectedness.

Table 1: Gravity Regressions – Aggregate Goods Trade in 2017

	Dependent variable: Aggregate Exports							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(SCI)		0.646***			0.277***		0.280***	0.284***
		(0.039)			(0.022)		(0.026)	(0.024)
log(Distance)			-0.992***		-0.695***	-0.888***	-0.614***	
			(0.060)		(0.071)	(0.055)	(0.063)	
Common Border				1.777***		0.371***	0.367***	0.465***
				(0.226)		(0.114)	(0.101)	(0.094)
Common Official Language				0.151		0.055	-0.130	-0.059
				(0.147)		(0.099)	(0.085)	(0.073)
Common Colonizer				1.001***		0.244*	0.058	0.150
				(0.156)		(0.146)	(0.145)	(0.113)
Colonial Relationship				0.332		-0.259	-0.262	-0.213
				(0.251)		(0.375)	(0.304)	(0.292)
Orig. and Dest. Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Distance Group Controls								Y
R^2	0.837	0.921	0.935	0.894	0.941	0.937	0.943	0.947
N	27,060	27,060	27,060	27,060	27,060	27,060	27,060	27,060

Note: Table shows results from regression 2, estimated using PPML. The dependent variable is total exports from country *i* to country *j* in 2017. Controls include the logarithm of SCI, the logarithm of distance, a common border dummy, a common official language dummy, a dummy indicating whether the two countries had a common colonizer post-1945, a dummy indicating whether the pair of countries was in a colonial relationship post-1945. All specifications include fixed effects for the importer and exporter country. Distance group controls correspond to dummies for percentiles of the distance distribution. Standard errors are clustered by exporter and importer country. The data include 165 countries and 27,060 (= 165 x 164) observations. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

In column 3, we remove the control for social connectedness, and instead include controls for the geographic distance between countries. The elasticity of trade with respect to distance is -0.99. This magnitude is consistent with estimates in prior work (see Head and Mayer, 2014). The increase in the R^2 relative to the specification in column 1 is similar in magnitude to the increase from including social connectedness. Column 4 adds to the specification in column 1 a number of other gravity variables that the literature has focused on (see Anderson and Van Wincoop, 2003; Head and Mayer, 2014). Sharing a border, a colonizer, a language, and a colonial relationship all increase bilateral trade. However, these gravity variables jointly explain a smaller share of the cross-sectional variation in trade flows than social connectedness or distance do.

In column 5, we control for both social connectedness and geographic distance. Due to the correlation between these two variables, the elasticity of trade to social connectedness drops from 0.65 to 0.28, and the distance elasticity drops from -0.99 to -0.70. The additional control for social connectedness increases the R^2 by 0.6% relative to that in column 3, which only included controls for distance in addition to importer and exporter fixed effects. This increase in the R^2 corresponds to about 8% of the variation not already explained by distance and fixed effects, and is larger than the incremental variation explained by the other gravity variables (see column 6). The decline in the distance elasticity from adding controls for social connectedness between columns 3 and 5 is substantial. This finding relates to an important literature that has argued that the estimated effect of distance on trade is too large and time-invariant to primarily capture trading costs (see Disdier and Head, 2008; Head and Mayer, 2014). This literature has proposed that geographic distance might instead be proxying for some other frictions such as information frictions (e.g., Rauch, 2001; Rauch and Trindade, 2002). Since social connectedness can help overcome many of these frictions, our evidence here and in the rest of this paper is highly consistent with this interpretation of the baseline magnitude of the distance elasticity.

In column 7, we jointly control for social connectedness, geographic distance, and other gravity variables. The results highlight that social connectedness explains variation in bilateral trade flows beyond these other predictors. Interestingly, the estimated elasticity of trade with respect to social connectedness remains unchanged relative to the estimates from column 5, even though the newly added gravity variables are correlated with social connectedness. Quantitatively we find that, even after controlling for a host of control variables that potentially proxy for various aspects of social connectedness, a doubling of social connectedness between two countries is associated with a 28% increase in trade flows.

The main object of interest in much of this paper is the elasticity between trade and social connectedness. To show that this elasticity is not picking up some non-linear relationship between log-distance and log-trade flows, the specification estimated in column 8 replaces our control for log-distance with dummy variables for each percentile of the distance distribution, allowing us to control for geographic distance in a highly non-linear way. The estimate of the relationship between social connectedness and trade flows is nearly identical to that in column 7.

While the analysis presented in Table 1 only explores trade flows in 2017, in Appendix B.3 we show that the relationship between trade and the *Social Connectedness Index* is similar when measuring trade flows in every year since 1980. This evidence shows that the observed relationships are not reflecting a causal effect of Facebook links per se—since Facebook as a company was only founded in 2004—and are more consistent with our interpretation that Facebook friendship links allow us to measure important underlying trade-facilitating relationships in a systematic way. In addition, these findings suggest that these trade-facilitating relationships across countries are highly stable over time.

Mechanism Through Which Social Connectedness Can Affect Trade Patterns.

We now turn to understanding the mechanisms behind the positive relationship between social connectedness and trade flows. A first channel through which social connections might facilitate trade is by reducing information frictions. For example, social connectedness can mitigate search costs by allowing importers and exporters to share information about prices and products.[10] In an influential paper, Rauch (1999) argues that these search costs are lower for goods that are traded on organized exchanges, since those goods are more homogeneous and their prices more transparent. If social connectedness helped facilitate trade in part by reducing information frictions, we would thus expect a larger elasticity of trade to social connectedness among those goods that are not traded on exchanges.

A second source of trade barriers that might be mitigated through social connections are contract enforcement frictions. Anderson and Marcouiller (2002) show that weak institutions in the importing country substantially decreases trade (see also Berkowitz et al., 2006; Levchenko, 2007; Nunn, 2007). In the absence of strong institutional enforcement of contracts, Greif (1989, 1993); Rauch (2001); Rauch and Trindade (2002); Combes et al. (2005); Ranjan and Lee (2007), and others have argued that social linkages and ethnic networks can facilitate trade by providing reputation-based punishment for contract violations. We therefore also explore whether the elasticity of trade to social connectedness is larger between trading partners with a weaker rule of law.

For these analyses, we use more disaggregated trade data, allowing us to explore heterogeneity across different products. The unit of observation is exports of product k from country i to country j. A product corresponds to one of 96 unique 2-digit HS96 categories. We estimate the following regression:

$$\begin{aligned} X_{i,j,k} = \exp[&\beta_1 \log(SCI_{i,j}) + \beta_2 \log(SCI_{i,j}) \cdot ET_k + \\ &\beta_3 \log(SCI_{i,j}) \cdot RL_i + \beta_4 \log(SCI_{i,j}) \cdot RL_j + \beta_5 G_{i,j,k}] \cdot \epsilon_{i,j,k}. \end{aligned} \tag{3}$$

ET_k is the fraction of exchange traded goods in each 2-digit HS96 product category k.[11] RL_i and RL_j are continuous measures of the rule of law in the exporting and importing countries, as measured by the World Governance Indicators (Kaufmann et al., 2011) as of 2017.[12] As before, $G_{i,j,k}$ are a set of gravity variables and fixed effects. All specifications include origin country $\times$ product and destination country $\times$ product fixed effects, allowing us to control for differences in country-specific factor endowments. Additionally, product-specific distance controls account for the fact that different products have different shipping costs per unit of distance (see the discussion in Rauch, 1999).

We present the results from estimating regression 3 in Table 2. Column 1 shows our baseline specification from column 7 of Table 1 for product-level trade data. The estimated elasticity of trade with respect to social connectedness (as well as the unreported coefficients on the other gravity variables) are very

[10] A similar mechanism has been proposed in the literature studying the effects of immigration on trade and FDI (see Wagner et al., 2002; Dunlevy, 2006; Felbermayr and Toubal, 2012; Burchardi et al., 2016).

[11] To construct this measure, we start from trade data at the 6-digit HS96 level, and use the "conservative" classification scheme by Rauch (1999) to classify goods into "exchange-traded" and "not exchange-traded"; the results are similar using the "liberal" classification. We then calculate the fraction of exchange-traded goods at the 2-digit HS96 level using the total global share of trade in those goods in each 2-digit category. Across products, ET_k ranges from 0 to 0.91, with a mean of 0.12, and a standard deviation of 0.25. To provide a sense of the variation, within category HS-19 (preparations of cereals, flour, starch or milk such as pastry products), 0% of goods are exchange-traded; within category HS-27 (mineral fuels, oils, and products of their distillation), 44% are exchange-traded; and within category HS-80 (tin and articles thereof), 90% are exchange-traded.

[12] This measure captures "perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence." The measure ranges between −2.5 and 2.5. Across countries, it has a mean of −0.06, and a standard deviation of 0.99. Venezuela has a score of −2.3, Mexico has a score of −0.57, the U.S. has a score of 1.64, and Finland has a score of 2.0.

Table 2: Gravity Regressions – Goods Trade Heterogeneity in 2017

	Dependent variable: Product-Specific Exports				
	(1)	(2)	(3)	(4)	(5)
log(SCI)	0.275***	0.299***	0.304***	0.281***	0.287***
	(0.027)	(0.028)	(0.024)	(0.031)	(0.025)
log(SCI) × Share Exchange-Traded		-0.179**	-0.148**		
		(0.080)	(0.070)		
log(SCI) × Rule of Law Destination				-0.014	-0.010
				(0.021)	(0.019)
log(SCI) × Rule of Law Origin				0.000	0.005
				(0.019)	(0.015)
Origin Country × Product FE	Y	Y	Y	Y	Y
Destination Country × Product FE	Y	Y	Y	Y	Y
Other Gravity Controls	Y	Y	Y	Y	Y
log(Distance) × Product FE	Y	Y		Y	
Distance Group × Product FE			Y		Y
R^2	0.932	0.933	0.946	0.932	0.946
N	2,597,760	2,597,760	2,597,760	2,597,760	2,597,760
N - Explained by FE	334,186	334,186	334,186	405,093	405,093

Note: Table shows results from regression 3. The dependent variable is exports of product category k from country i to country j in 2017. Product-level trade data are aggregated up to the first 2 digits of the HS96 product classification. Other gravity controls include a common border dummy, a common official language dummy, a dummy indicating whether the two countries had a common colonizer post-1945, and a dummy indicating whether the pair of countries was in a colonial relationship post-1945. We also separately control for the logarithm of distance interacted with product categories in columns 1, 2, 4 and for distance groups (dummies for percentiles of the distance distribution) interacted with product categories in columns 3 and 5. Share Exchange-Traded refers to the proportion of exchange-traded products—based on the conservative classification scheme in Rauch (1999)—within a product category. Rule of law is obtained from the World Governance Indicators published by the World Bank. All specifications include fixed effects for the importer and exporter country interacted with product categories. Standard errors are clustered by exporter and importer country. The data include 165 countries and 96 product categories, which amounts to 2,597,760 observations. Observations that are fully explained by the fixed effects are dropped before the PPML estimation. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

similar to our baseline specification presented in Table 1. In column 2, we interact $\log(SCI_{i,j})$ with the fraction of exchange-traded products in each product category. The coefficient on this interaction is -0.18, suggesting that social connectedness matters substantially less for trade in product categories that have more exchange-traded goods. Quantitatively, the elasticity is more than twice as large in a category with no exchange-traded goods than it is in a category with primarily exchange-traded goods. This finding provides suggestive evidence that one of the channels through which social connectedness facilitates trade is by decreasing information frictions, which are smaller for exchange-traded goods. In column 3, rather than using product-specific interactions with $log(Distance_{i,j})$, we interact 100 dummies for quantiles of distance with product dummies to allow for a separate non-linear effect of distance on each product's trade. The results are essentially unchanged in this specification.

Columns 4 and 5 interact our measures of the rule of law in the destination and origin countries with the social connectedness across country pairs. Column 4 controls for product-specific effects of

$log(Distance_{i,j})$, and column 5 includes non-linear product-specific distance controls. In both specifications, we find little variation in the elasticity of trade with respect to the rule of law in either the origin or destination country. This suggests that the primary channel through which social connectedness as measured by the *Social Connectedness Index* influences trade patterns is by mitigating information frictions, with at most a small role played by reductions in contract enforcement frictions.[13]

3 Trade and Subnational Social Connectedness in Europe

In the previous section, we explored the relationship between social connectedness and trade across countries. Our preferred interpretation of that evidence is that the *Social Connectedness Index* measures real-world social networks that help facilitate trade by reducing information frictions. In this section, we further analyze how social connectedness influences trade patterns. To do so, we exploit the granular nature of the *Social Connectedness Index* and study trade and connectedness across subnational European regions. By focusing on Europe, we can zoom in on the patterns of social connections that influence trade in specific products and relate them to the geographic distribution of production. We conduct two separate analyses along these lines.

In Section 3.1, we construct product-specific measures of across-country social connectedess. These measures weight the connectedness of subnational region pairs by the importance that these regions should have for predicting exports of each product. These weights are based on where the good is produced in the exporting country and where it is used as an intermediate input in the importing country. We show that exports of each product vary primarily with these product-specific input-output-weighted measures of social connectedness between countries. In other words, what matters for trade in a specific good is not the average social connectedness across region pairs in the two countries. Instead, the social connections that predict trade in specific products are those between the regions where the product is produced in the exporting country and the regions where it is used in the importing country. Our findings in this section also allow us to rule out that the correlations between social connectedness and trade flows at the country level are driven by either reverse causality or by similar preferences between individuals in more connected countries.

In Section 3.2, we link regional social connectedness to data on rail freight volumes between those regions as a proxy for subnational trade flows. We find that social connectedness between regions matters for the trade between those regions, even after controlling for country pair fixed effects. This analysis allows us to control for many potential variables that might have been omitted from the aggregate country-level trade regressions in the previous section. In addition we find that the border effect—the empirical regularity that, all else equal, trade is higher between regions of the same country—declines dramatically once we control for social connectedness. This finding suggests that the baseline border effect is primarily driven by declines in social connectedness across borders.

[13]In addition to the evidence presented in the main body of the paper, the Appendix explores how being in a similar "social cluster" influences trade over and above bilateral social connections. Intuitively, sharing a similar social network could also reduce information frictions by decreasing search costs, whereby a common friend in a third country can pass information between potential trading partners. To study this potential channel, we use a clustering algorithm to group countries into non-overlapping clusters which each feature a high average within-cluster pairwise social connectedness. We then show that being in the same cluster increases bilateral trade between countries, over and above their direct pairwise social connectedness as well as standard gravity variables.

3.1 Input-Output-Weighted vs. Population-Weighted Social Connectedness

In Section 2, we related the volume of exports from country i to country j to the probability that a representative Facebook user in country i is friends with a representative Facebook user in country j, given by $SCI_{i,j}$. This measure of social connectedness is identical to a population-weighted average of the social connectedness across the regions in countries i and j. Formally, let us index the regions in each country i by $r_i \in R(i)$, let $Friendships_{r_i,r_j}$ count the total number of Facebook friendship links between individuals in regions r_i and r_j, let Pop_{r_i} denote the total (Facebook) population in region r_i, and let $PopShare_{r_i}$ denote the share of that population in region r_i in country i: $\sum_{r_i \in R(i)} PopShare_{r_i} = 1$. Then:

$$\begin{aligned}
SCI_{i,j} &= \frac{Friendships_{i,j}}{Pop_i \times Pop_j} = \frac{\sum\limits_{r_i \in R(i)} \sum\limits_{r_j \in R(j)} Friendships_{r_i,r_j}}{\left(\sum\limits_{r_i \in R(i)} Pop_{r_i}\right) \times \left(\sum\limits_{r_j \in R(i)} Pop_{r_j}\right)} \\
&= \sum_{r_i \in R(i)} \sum_{r_j \in R(j)} \frac{Pop_{r_i}}{\sum\limits_{r_i \in R(i)} Pop_{r_i}} \frac{Pop_{r_j}}{\sum\limits_{r_j \in R(j)} Pop_{r_j}} \frac{Friendships_{r_i,r_j}}{Pop_{r_i} \times Pop_{r_j}} \\
&= \sum_{r_i \in R(i)} \sum_{r_j \in R(j)} PopShare_{r_i} \times PopShare_{r_j} \times SCI_{r_i,r_j}. \qquad (4)
\end{aligned}$$

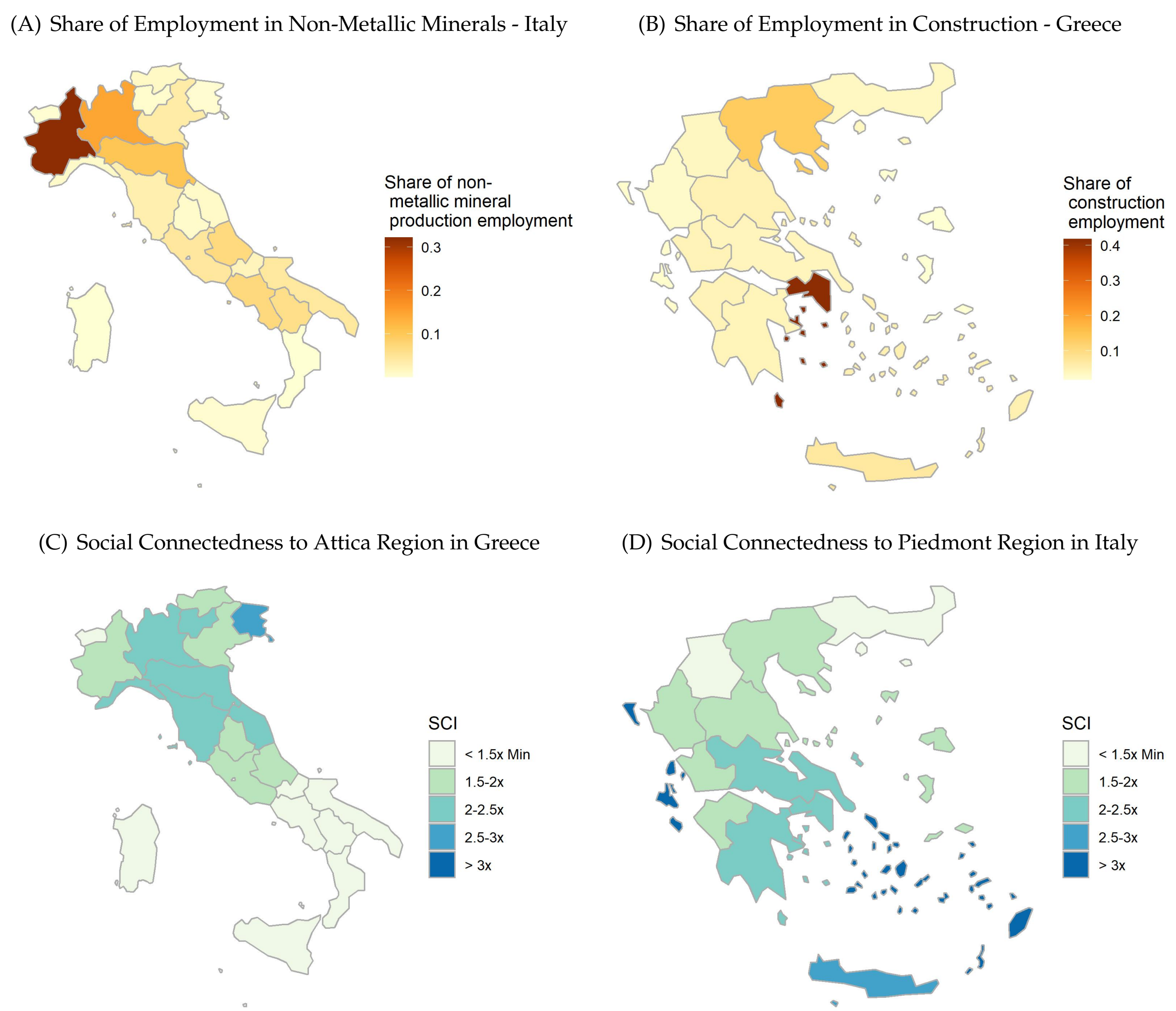
In other words, when previously exploring the role of $SCI_{i,j}$ as a determinant of trade between two countries, we implicitly imposed that the relative importance of the connectedness between different regions in explaining country-level trade increased with the population shares of those regions.

In this section, we propose that, for each good, the connectedness between the regions in country i where the good is produced and the regions in country j where the good is used might be particularly important for explaining exports of that good from country i to country j, in particular if these connections help mitigate information frictions. Our prediction that the social connections of individuals at the location of firms should matter disproportionately for predicting trade flows builds on the insights from a large literature that has documented that the vast majority of international trade is being conducted by a small set of firms (see Bernard et al., 2012, for a survey of this literature).

We find that the relative importance of regions in the production of goods often deviates substantially from their population weights, in particular for goods that are used as intermediate inputs in geographically clustered industries. Let us give a concrete example. More than 80% of Italian exports of non-metallic mineral products (e.g., cement) to Greece are used as inputs in the Greek construction sector. Panel A of Figure 3 shows the share of Italian employment in the sector that manufactures non-metallic mineral products in each of the country's NUTS2 regions. The largest share is in the northwestern Piedmont region, which includes the city of Torino. Similarly, Panel B of Figure 3 shows the share of Greek employment in the construction sector for each of the country's NUTS2 regions. The largest employment shares are in the Attica region covering metropolitan Athens. Based on this information, we propose that for exporting non-metallic mineral products from Italy to Greece, the connectedness between the Piedmont region and the Attica region should be particularly important, since firms located in those regions are most likely to be involved in any trade in this product. The bottom row of Figure

3 shows that there is substantial variation in which regions in Italy are connected to the Attica region in Greece (Panel C), and which regions in Greece are connected to the Piedmont region in Italy (Panel D). These figures highlight that the strongest social connections are not necessarily between the regions with firms that should matter most for the trading of non-metallic mineral products.

Figure 3: Regional Employment Shares And Social Connectedness



(A) Share of Employment in Non-Metallic Minerals - Italy

(B) Share of Employment in Construction - Greece

(C) Social Connectedness to Attica Region in Greece

(D) Social Connectedness to Piedmont Region in Italy

Note: Panel A plots the regional shares of employment in the non-metallic minerals industry across NUTS2 regions in Italy. Panel B plots the regional shares of employment in the construction sector across NUTS2 regions in Greece. Panels C and D, respectively, show heat maps of social connectedness from the Attica Region in Greece to Italian NUTS2 regions, and from the Piedmont Region in Italy to Greek NUTS2 regions.

We next test whether it is indeed the connections of those regions with firms most likely involved in trading a particular product that matter the most for explaining country-level trade in that product. To conduct this exercise, we construct, for each exporter $i \times$ importer $j \times$ product p triplet, the input-output-weighted social connectedness of regions in countries i and j that should be most important for predicting trade of product p. This construction involves a number of steps. First, since the trade data is at the product level, while the employment and input-output data is at the industry level, we match products in the trade data to industries (see Appendix C.1 for details). Accordingly, we will interchangeably refer to p as representing a product or an industry. For each product p produced in country i, we then use the World Input-Output Tables (WIOT) described in Timmer et al. (2015) to measure the share of that product that is used as an intermediate input in each industry p' in country j, $IO_{i,j}^{p,p'}$. We focus on uses of products as intermediate inputs, such that $\sum_{p'} IO_{i,j}^{p,p'} = 1$, and only consider products where at least 50% of the exports across countries in our sample are used as intermediate inputs (rather than in final consumption). This leaves us with a set P that includes 20 products, which we list in Appendix C.1. For each product $p \in P$, we then construct a measure of the social connectedness between countries i and j, $SCI_{i,j}^{p}$, that corresponds to the input-output-weighted average of the social connectedness between the NUTS2 regions in these countries that are most relevant for exporting product p from i to j:

$$SCI_{i,j}^{p} = \sum_{r_i \in R(i)} EmpShare_{p,r_i} \times \left[\sum_{p' \in P} IO_{i,j}^{p,p'} \times \left(\sum_{r_j \in R(j)} EmpShare_{p',r_j} \times SCI_{r_i,r_j} \right) \right]. \tag{5}$$

The variable $EmpShare_{p,r_i}$ represents the share of employment in industry p in country i that is in region r_i: $\sum_{r_i \in R(i)} EmpShare_{p,r_i} = 1$. These regional employment shares are constructed using data from Eurostat. We focus our analysis on 28 countries for which we have trade data, WIOT data, and regional employment data; these countries are reported in Appendix C.1.

Similarly, we construct a product-specific measure of the input-output-weighted geographic distance between each country, again under the maintained hypothesis that the geographic distance that should matter the most for exports in each country-pair-product is the distance between those regions where the product would be produced and used:

$$Distance_{i,j}^{p} = \sum_{r_i \in R(i)} EmpShare_{p,r_i} \times \left[\sum_{p' \in P} IO_{i,j}^{p,p'} \times \left(\sum_{r_j \in R(j)} EmpShare_{p',r_j} \times Distance_{r_i,r_j} \right) \right]. \tag{6}$$

Quantitatively, most of the cross-sectional variation in $SCI_{i,j}^{p}$ and $Distance_{i,j}^{p}$ comes from a common component that drives the social connectedness and geographic distance between all regions in a given country pair. For example, all regions of Germany are more connected to regions in Austria than they are to regions in Finland. Indeed, regressions of $SCI_{i,j}^{p}$ and $Distance_{i,j}^{p}$ on country i × country j fixed effects have R^2s above 90%. The remaining variation comes from the fact that, for some products, the producing or using industries are geographically concentrated in regions that might be differentially connected than the average region in a country pair. These differences provide the identifying variation in the following analyses.

We then explore how trade in different products correlates with the product-specific measures of social connectedness, $SCI_{i,j}^{p}$, and geographic distance, $Distance_{i,j}^{p}$, by estimating the following regression:

$$X_{i,j,p} = \exp[\beta_1 \log(SCI_{i,j}) + \beta_2 \log(Distance_{i,j}) + \beta_3 \log(SCI_{i,j}^{p}) + \beta_4 \log(Distance_{i,j}^{p}) + \delta_{i,j,p}] \cdot \epsilon_{i,j,p}. \tag{7}$$

Here, $X_{i,j,p}$ denotes the total value of exports of product p from country i to country j. We also include the logarithm of population-weighted measures of social connectedness and distance as controls; these are the same covariates that we used in Section 2. The vector $\delta_{i,j,p}$ represents various fixed effects. In all specifications we add country $i \times$ product p fixed effects as well as country $j \times$ product p fixed effects, which controls for the average propensity of each country to export and import each good.

Table 3 shows results from regression 7. In column 1, we control only for the population-weighted social connectedness and distance. The estimated elasticity of trade to social connectedness is similar to that estimated in Section 2. This suggests that the set of countries and products for which we can construct input-output-weighted social connectedness has similar trade elasticities to the full sample of countries. In column 2, we instead control for the product-specific input-output-weighted social connectedness between countries i and j. The magnitudes of the trade elasticities are similar to those in column 1. As discussed above, this is consistent with the fact that much of the regional variation in social connectedness is explained by a component that is common for all region pairs in a country pair. In column 3, we control for both the population-weighted and input-output-weighted measures of social connectedness. While these two objects have a correlation of 95%, the regression loads strongly on the input-output-weighted measure of social connectedness—once this is controlled for, the population-weighted social connectedness has no additional predictive power. This finding suggests that what matters for the trade in a specific product is the social connectedness across the regions that produce and use that specific good, instead of the social connectedness across the most heavily populated regions.

In columns 4 and 5, we include fixed effects for each country pair; relative to the specification in column 4, in column 5 we replace the linear control for $\log(Distance^{p}_{i,j})$ with dummies for percentiles of the distribution of that variable. The newly introduced country pair fixed effects fully absorb the population-weighted social connectedness and geographic distance between country pairs. Importantly, the inclusion of these fixed effects also controls for any other observable or unobservable factors that might have been correlated with both social connectedness and trade flows for a given country pair, and which would have thus caused an omitted variables bias in the previous regressions. For example, including country pair fixed effects controls for whether countries share a common language, a common religion, or a common historical origin, all of which might be correlated both with trade flows and social connectedness. The estimated elasticity of trade flows to the product-specific input-output-weighted social connectedness is essentially unchanged in this specification.[14]

One specific concern alleviated by the specifications in columns 4 and 5 of Table 3 is that the correlation between country-level social connectedness and trade documented in Section 2 might be the result of common preferences in consumption. Under this alternative theory, higher social connectedness between the populations of two countries coincides with more similar consumption preferences of the populations, for example because social connectedness is partially driven by migration, and migrants have similar preferences to people in their countries of origin. This similiarity of preferences might then be the source of trade in both final consumption goods and intermediate goods used in the production of the consumption goods (see Linder, 1961). However, if such an omitted variable explained the patterns in Section 2, the population-weighted social connectedness across regions would be the most powerful

[14] In Appendix C.3, we use a randomization inference approach to provide additional evidence that the social connections that determine trade in specific products are those between the regions where the product is produced in the exporting country and the regions where it is used in the importing country.

Table 3: Input-Output-Weighted Social Connectedness and Trade in 2017

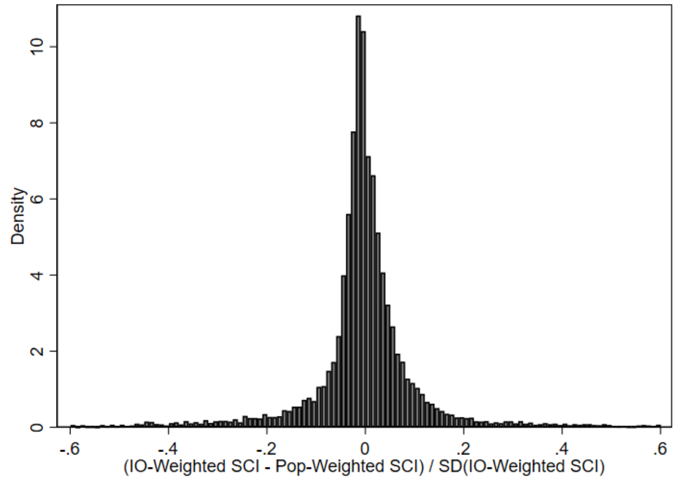
	Dependent variable: Product-Specific Bilateral Trade						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(SCI)	0.279***		-0.037				
	(0.022)		(0.123)				
log(Distance)	-0.975***		-0.365*				
	(0.052)		(0.203)				
log(SCI^p)		0.255***	0.296**	0.303**	0.333**	0.268*	0.424***
		(0.022)	(0.125)	(0.148)	(0.139)	(0.154)	(0.149)
log($Distance^p$)		-0.944***	-0.588***	-1.020***		-0.305	
		(0.052)	(0.196)	(0.196)		(0.303)	
Origin Country × Product FE	Y	Y	Y	Y	Y	Y	Y
Destination Country × Product FE	Y	Y	Y	Y	Y	Y	Y
Undir. Country Pair FE				Y	Y		
log($Distance^p$) Group FE					Y		Y
Undir. Country Pair × Product FE						Y	Y
R^2	0.953	0.955	0.955	0.970	0.971	0.990	0.991
N	15,120	15,120	15,120	15,120	15,120	15,120	15,120
N - Explained by FE	262	591	591	591	591	2,488	2,488

Note: Table shows the results from regression 7. The dependent variable is exports of product k from country i to country j in 2017. The variable $\text{SCI}_{i,j}$ is the population-weighted average of NUTS2 region-level social connectedness. The variable $\text{SCI}_{i,j}^p$ is an employment share-weighted measure as defined in equation 5. The measures $\text{Distance}_{i,j}$ and $\text{Distance}_{i,j}^p$ are constructed in the same way as the corresponding social connectedness measures. All specifications include origin country × product and destination country × product fixed effects. Columns 4 and 5 add country pair fixed effects that do not distinguish the direction of trade (undirected). Columns 6 and 7 include fixed effects that interact the undirected country pair fixed effects with product fixed effects. In columns 5 and 7, we replace the control for log($\text{Distance}_{i,j}^p$) with 100 dummy variables representing percentiles of the distance distribution. Standard errors are clustered by origin × destination country pair. The data include 28 countries and 20 products leading to 15,120 (= 28 × 27 × 20) observations. Observations that are fully explained by the fixed effects are dropped before the PPML estimation. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

predictor of trade between countries, since it provides the most appropriate measure of the similarity of preferences between the populations. In contrast, we find that it is the social connectedness between the locations of output and input industries for each product that determines the amount of trade. This finding suggests that similarities in preferences between more connected countries does not constitute a quantitatively important determinant of trade within Europe.

In columns 6 and 7 of Table 3, we include fixed effects that interact each product type with undirected country i × country j pair fixed effects: in other words, we are comparing exports of a specific good from country i to country j to the exports of the same good from country j to country i. The remaining variation in product-specific social connectedness comes from the fact that the industries that produce the product in each country are not located in the same regions as the industries that use these

Figure 4: Ruling Out Reverse Causality



Note: Figure shows the distribution of the difference between the input-output-weighted social connectedness and the population-weighted social connectedness. More specifically, for each country i × country j × product p triplet, we construct the input-output-weighted social connectedness $SCI^p_{i,j}$, then subtract the population-weighted social connectedness $SCI^p_{i,j}$ and divide by the cross-sectional standard deviation of $SCI^p_{i,j}$, as specified in equation 8.

products as an input: $\text{SCI}^{p'}_{i,j} \neq \text{SCI}^{p'}_{j,i}$. The inclusion of these fixed effects does not have a systematic effect on the estimate of the elasticity of trade with respect to social conectedness, providing further evidence that common preferences across countries (which would likely affect the trade of a given good in both directions) are not a large driver of the findings in Section 2.

Ruling out Reverse Causality. Another benefit of exploring the input-output-weighted social connectedness is that it allows us to further address concerns regarding reverse causality as an explanation for the observed relationship between trade and social connectedness, whereby the observed social connections are formed as a result of social interactions due to trade. Our approach starts from the observation that, under the reverse causality story, the social connectedness between input-output-weighted regions should be systematically larger in magnitude than the social connectedness between population-weighted regions, since reverse causality would increase the connectedness between those regions that are actually engaged in trade relative to the connectedness of other regions not engaged in trade. To test whether this is indeed the case, we construct for each country i × country j × product p triplet the difference between the input-output-weighted social connectedness and the population-weighted social connectedness across countries i and j. To interpret the magnitude of the differences, we express them as a fraction of the cross-sectional standard deviation of $SCI^p_{i,j}$:

$$SCI\_Divergence^p_{i,j} = \frac{SCI^p_{i,j} - SCI_{i,j}}{SD(SCI^p_{i,j})}. \tag{8}$$

Figure 4 shows a histogram of $SCI\_Divergence^p_{i,j}$ across all 15,120 country i × country j × product p triplets. The distribution has a mean of 0.008, and a median of -0.003. In other words, the regions that were shown to be most important for the trade in a given product are equally likely to be more connected or less connected than the population-weighted average of regions across a country pair. This provides strong evidence against a quantitatively large reverse causality story in which the fact that two regions trade more with each other causes them to be meaningfully more socially connected.

3.2 Subnational Social Connectedness, Rail Freight Flows, and the Border Effect in Trade

In the final part of the paper, we study the relationship between regional social connectedness and subnational trade flows. This analysis allows us to examine the determinants of the border effect—the empirical regularity that, conditional on the distance between two regions, trade is much larger between regions that are part of the same country (see McCallum, 1995; Anderson and Van Wincoop, 2003).

A common challenge for exploring the border effect is the absence of systematic and large-scale trade data at the subnational level. However, within Europe, we observe data on rail freight tonnage shipped in 2015 between pairs of NUTS2 regions for a number of countries (rail freight transport accounted for 12.2% of all intra-EU freight transport in 2015).[15] We explore the relationship between rail freight flows and social connectedness across European NUTS2 regions using the following regression:

$$RailFreight_{r_i,r_j} = \exp[\beta_1 \log(SCI_{r_i,r_j}) + \beta_2 \log(Distance_{r_i,r_j}) + \beta_3 \mathbb{1}^{SameCountry}_{r_i,r_j} + \delta_{r_i,r_j}] \cdot \epsilon_{r_i,r_j}. \quad (9)$$

The dependent variable, $RailFreight_{r_i,r_j}$, is the amount of goods (in tons) shipped by rail from region r_i to region r_j. The variables $\log(SCI_{r_i,r_j})$ and $\log(Distance_{r_i,r_j})$ are the logarithms of the social connectedness and distance between NUTS2 regions, respectively, and δ_{r_i,r_j} represents various fixed effects. The dummy variable $\mathbb{1}^{SameCountry}_{r_i,r_j}$ captures whether region r_i and region r_j are part of the same country.

Table 4 presents the results from regression 9. Column 1 does not yet control for the social connectedness between regions. Conditional on geographic distance, trade is about nine times larger between regions in the same country than between regions in different countries. This estimate is the same order of magnitude as that of Chen (2004), who finds that EU countries trade about six times more with themselves than with other countries, and that of Tan (2016), who finds that truck freight shipments in Europe are 5.75 times higher for shipments within the same country. These estimated border effects are large in light of the fact that most countries in the sample are part of the European Common Market, and therefore face no formal barriers to trade such as tariffs; indeed, we find similar border effects when we restrict our sample to exclusively focus on NUTS2 regions from countries within the single market.

In column 2, we include our measure of the social connectedness between regions. The elasticity of trade flows with respect to social connectedness is similar to that estimated at the country level above. The estimate of trade declines at the border drop dramatically, from a border effect of 918% to a border effect of about 307%, a decline of more than 65%. In columns 3 and 4, we conduct the same analysis as in columns 1 and 2, but replace our controls for geographic distance with dummy variables for percentiles of the distance distribution. This ensures that the estimated border effect does not, in part, pick

[15] We use data on region-to-region rail goods transport made available by Eurostat in the series *tran_rt_rago*. The data are built from individual country reports to the European Union on national and international rail transport in 2015. For each pair of NUTS2 regions r_i and r_j, the data include the tons of goods that were loaded on a railway vehicle in region r_i and unloaded in region r_j. We take a number of steps to standardize and clean the data, as described in Appendix C.2.

up non-linearities in the relationship between geographic distance and trade. In these specifications, the magnitude of the border effect declines even more after the inclusion of controls for social connectedness, from 735% to 63%, an estimate that is barely significant at the 10% level. These findings suggest that much of the reason we see border effects in trade is that social connectedness is much stronger across regions within countries than it is across equidistant regions in different countries.

Table 4: Subnational Social Connectedness and the Border Effect – Rail Trade 2015

	Dependent variable: Regional Bilateral Rail Freight							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(SCI)		0.425***		0.533***	0.343***	0.369***	0.457***	0.425***
		(0.058)		(0.048)	(0.088)	(0.122)	(0.088)	(0.110)
log(Distance)	-1.383***	-0.882***			-0.632***	-0.539**		
	(0.124)	(0.125)			(0.166)	(0.240)		
Same Country	2.218***	1.123***	1.986***	0.493*				
	(0.240)	(0.265)	(0.221)	(0.272)				
Orig. and Dest. Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Distance Group FE			Y	Y			Y	Y
Undir. Country Pair FE					Y		Y	
Orig. Reg. x Dest. Ctry FE						Y		Y
Dest. Reg. x Orig. Ctry FE						Y		Y
R^2	0.759	0.767	0.777	0.789	0.795	0.839	0.805	0.844
N	74,862	74,862	74,862	74,862	74,862	74,862	74,862	74,862
N - Explained by FE	27,442	27,442	32,934	32,934	47,350	58,282	47,593	59,304

Note: Table shows the results from regression 9. The dependent variable is the rail freight shipped from NUTS2 region r_i to NUTS2 region r_j in 2015. "Same Country" is a dummy variable indicating whether the rail shipment is between NUTS2 regions within the same country. All specifications include origin region and destination region fixed effects. Columns 3, 4, 7, and 8 include dummy variables for percentiles of the distance distribution. Columns 5 and 7 add country pair fixed effects that do not distinguish the direction of trade. Columns 6 and 8 add origin region $\times$ destination country and destination region $\times$ origin country fixed effects. Standard errors are clustered by NUTS2 origin region and NUTS2 destination region. The data contains 332 NUTS2 regions and 74,862 non-missing trade observations. Observations that are fully explained by the fixed effects are dropped before the PPML estimation. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

In column 5, we add country pair fixed effects to the specification in column 2. As before, this controls for any differences across country pairs that might affect trade between regions of these countries, and that might be correlated with social connectedness (e.g., common language, common history, or common tastes). The estimated elasticity of trade flows to social connectedness barely changes, confirming our earlier conclusion that country-pair-level omitted variables that might correlate with social connectedness are not a key driver of our results. However, within Europe, some of these omitted variables do not just vary at the country pair level, but can also vary at the region-country level. For example, the Alsace region in France has common historical heritage with regions in Germany (for example, during the Franco-Prussian war, France ceded Alsace to the German Empire, while the Treaty of Versailles ceded it back to France). Similarly, the Zentralschweiz region of Switzerland has a common language with Germany, while the Lake Geneva region shares a common language with France. To control for such determinants of trade at the region-country level, column 6 includes origin region $\times$ destination country and destination region × origin country fixed effects. The estimated elasticity of trade to social connectedness is again unaffected, though standard errors increase as our fixed effects remove more and more of the cross-sectional variation in SCI_{r_i,r_j}. Again, these estimates suggest that our central findings are not confounded by omitted variables bias. The estimates in columns 7 and 8, which include non-parametric controls for the geographic distance between regions, confirm this finding.

4 Conclusion

In this paper, we use de-identified data from Facebook to construct a comprehensive measure of the social connectedness between countries and between subnational regions. We use this measure to study the relationship between social connectedness and trade flows. Our findings on how social connections shape trade patterns provide new evidence for how social interactions can determine financial and economic outcomes (see Hirshleifer, 2020; Kuchler and Stroebel, 2020).

We hope that our easily accessible measures of social connectedness will be used to broaden our understanding of the economic effects of social networks across a range of settings beyond international trade. For example, an exciting theoretical literature suggests that social interactions shape financial market outcomes (Akcay and Hirshleifer, 2020; Hirshleifer, 2020) and that the diversity of social networks is an important determinant of economic development; conversely, tightly clustered social ties can limit access to a broad range of social and economic opportunities (for example Granovetter, 1977, 2005; Chetty et al., 2020). Our data can help researchers test these and other predictions on the relationship between social structure and socio-economic outcomes. More generally, our research emphasizes the increasingly important role of data from online services—such as Facebook, LinkedIn, Twitter, eBay, Mint, Trulia, and Zillow—in overcoming important measurement challenges across the social sciences (see, for example, Baker, 2018; Giglio et al., 2015; Einav et al., 2015; Piazzesi et al., 2015; Bailey et al., 2020b).

References

Erol Akcay and David Hirshleifer. Social transmission bias and cultural evolution in financial markets. Technical report, National Bureau of Economic Research, 2020.

Jenny C Aker. Information from markets near and far: Mobile phones and agricultural markets in niger. *American Economic Journal: Applied Economics*, 2(3):46–59, 2010.

Alberto Alesina, Arnaud Devleeschauwer, William Easterly, Sergio Kurlat, and Romain Wacziarg. Fractionalization. *Journal of Economic Growth*, 8(2):155–194, 2003.

Treb Allen. Information frictions in trade. *Econometrica*, 82(6):2041–2083, 2014.

James E Anderson and Douglas Marcouiller. Insecurity and the pattern of trade: An empirical investigation. *Review of Economics and Statistics*, 84(2):342–352, 2002.

James E Anderson and Eric Van Wincoop. Gravity with gravitas: a solution to the border puzzle. *American Economic Review*, 93(1):170–192, 2003.

Michael Bailey, Rachel Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong. Social connectedness: Measurement, determinants, and effects. *Journal of Economic Perspectives*, 32(3):259–80, 2018a.

Michael Bailey, Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel. The economic effects of social networks: Evidence from the housing market. *Journal of Political Economy*, 126(6):2224–2276, 2018b.

Michael Bailey, Eduardo Dávila, Theresa Kuchler, and Johannes Stroebel. House price beliefs and mortgage leverage choice. Technical Report 6, 2019a.

Michael Bailey, Drew M Johnston, Theresa Kuchler, Johannes Stroebel, and Arlene Wong. Peer effects in product adoption. Technical report, National Bureau of Economic Research, 2019b.

Michael Bailey, Patrick Farrell, Theresa Kuchler, and Johannes Stroebel. Social connectedness in urban areas. *Journal of Urban Economics*, page 103264, 2020a.

Michael Bailey, Drew Johnston, Martin Koenen, Theresa Kuchler, Dominic Russel, and Johannes Stroebel. Social distancing during a pandemic: The role of friends. Working paper, National Bureau of Economic Research, 2020b.

Michael Bailey, Drew Johnston, Theresa Kuchler, Dominic Russel, Johannes Stroebel, et al. The determinants of social connectedness in europe. In *International Conference on Social Informatics*, pages 1–14. Springer, 2020c.

Scott R Baker. Debt and the response to household income shocks: Validation and application of linked financial account data. *Journal of Political Economy*, 126(4):1504–1557, 2018.

Richard Baldwin and James Harrigan. Zeros, quality, and space: Trade theory and trade evidence. *American Economic Journal: Microeconomics*, 3(2):60–88, 2011.

Turan G Bali, David A Hirshleifer, Lin Peng, and Yi Tang. Attention, social interaction, and investor attraction to lottery stocks. In *9th Miami Behavioral Finance Conference*, 2018.

Daniel Berkowitz, Johannes Moenius, and Katharina Pistor. Trade, law, and product complexity. *Review of Economics and Statistics*, 88(2):363–373, 2006.

Andrew B Bernard, Jonathan Eaton, J Bradford Jensen, and Samuel Kortum. Plants and productivity in international trade. *American Economic Review*, 93(4):1268–1290, 2003.

Andrew B Bernard, J Bradford Jensen, Stephen J Redding, and Peter K Schott. Firms in international trade. *Journal of Economic Perspectives*, 21(3):105–130, 2007.

Andrew B Bernard, J Bradford Jensen, Stephen J Redding, and Peter K Schott. The empirics of firm heterogeneity and international trade. *Annual Review of Economics*, 4(1):283–313, 2012.

Antoine Berthou and Charlotte Emlinger. The trade unit values database. *Economie Internationale*, (4): 97–117, 2011.

Konrad B Burchardi, Thomas Chaney, and Tarek A Hassan. Migrants, ancestors, and investments. Technical report, 2016.

Thomas Chaney. Distorted gravity: the intensive and extensive margins of international trade. *American Economic Review*, 98(4):1707–21, 2008.

Thomas Chaney. The network structure of international trade. *American Economic Review*, 104(11):3600–3634, 2014.

Thomas Chaney. Networks in international trade. In *The Oxford Handbook of The Economics of Networks*. 2016.

Thomas Chaney. The gravity equation in international trade: An explanation. *Journal of Political Economy*, 126(1):150–177, 2018.

Natalie Chen. Intra-national versus international trade in the european union: why do national borders matter? *Journal of International Economics*, 63(1):93–118, 2004.

Raj Chetty, Nathaniel Hendren, Matthew O. Jackson, Theresa Kuchler, and Johannes et al. Stroebel. Social capital in the united states: Measurement, determinants, and associations with economic mobility. Working paper, 2020.

Pierre-Philippe Combes, Miren Lafourcade, and Thierry Mayer. The trade-creating effects of business and social networks: evidence from france. *Journal of International Economics*, 66(1):1–29, 2005.

Sergio Correia, Paulo Guimarães, and Thomas Zylkin. Verifying the existence of maximum likelihood estimates for generalized linear models. 2019a.

Sergio Correia, Paulo Guimarães, and Thomas Zylkin. ppmlhdfe: Fast Poisson Estimation with High-Dimensional Fixed Effects. 2019b.

Kingsley Davis. The population of india and pakistan. 1951.

Anne-Célia Disdier and Keith Head. The puzzling persistence of the distance effect on bilateral trade. *The Review of Economics and Statistics*, 90(1):37–48, 2008.

Maeve Duggan, Nicole B Ellison, Cliff Lampe, Amanda Lenhart, and Mary Madden. Social media update 2014. pew research center., January 2015.

Maeve Duggan, Shannon Greenwood, and Andrew Perrin. Social media update 2016. Pew Research Center., November 2016.

James A Dunlevy. The influence of corruption and language on the protrade effect of immigrants: Evidence from the american states. *Review of Economics and Statistics*, 88(1):182–186, 2006.

Jonathan Eaton and Samuel Kortum. Technology, geography, and trade. *Econometrica*, 70(5):1741–1779, 2002.

Liran Einav, Theresa Kuchler, Jonathan Levin, and Neel Sundaresan. Assessing sale strategies in online markets using matched listings. *American Economic Journal: Microeconomics*, 7(2):215–47, 2015.

Robert C Feenstra and John Romalis. International prices and endogenous quality. *The Quarterly Journal of Economics*, 129(2):477–527, 2014.

Gabriel J Felbermayr and Farid Toubal. Revisiting the trade-migration nexus: Evidence from new oecd data. *World Development*, 40(5):928–937, 2012.

Guillaume Gaulier and Soledad Zignago. Baci: international trade database at the product-level (the 1994-2007 version). 2010.

Stefano Giglio, Matteo Maggiori, Johannes Stroebel, and Andreas Weber. Climate change and long-run discount rates: Evidence from real estate. Technical report, 2015.

Mark Granovetter. The impact of social structure on economic outcomes. *The Journal of Economic Perspectives*, 19(1):33–50, 2005.

Mark S Granovetter. The strength of weak ties. In *Social networks*, pages 347–367. Elsevier, 1977.

Avner Greif. Reputation and coalitions in medieval trade: evidence on the maghribi traders. *The Journal of Economic History*, 49(4):857–882, 1989.

Avner Greif. Contract enforceability and economic institutions in early trade: The maghribi traders' coalition. *The American Economic Review*, pages 525–548, 1993.

Juan Carlos Hallak. Product quality and the direction of trade. *Journal of International Economics*, 68(1): 238–265, 2006.

Juan Carlos Hallak and Peter K Schott. Estimating cross-country differences in product quality. *The Quarterly Journal of Economics*, 126(1):417–474, 2011.

Keith Head and Thierry Mayer. Gravity equations: Workhorse, toolkit, and cookbook. In *Handbook of International Economics*, volume 4, pages 131–195. Elsevier, 2014.

Elhanan Helpman, Marc Melitz, and Yona Rubinstein. Estimating trade flows: Trading partners and trading volumes. *The Quarterly Journal of Economics*, 123(2):441–487, 2008.

David Hirshleifer. Presidential address: Social transmission bias in economics and finance. *The Journal of Finance*, 2020.

David Hirshleifer, Lin Peng, and Wang Qiguang. Social interaction and market reaction to earnings news. Technical report, Technical report, Working Paper, 2019.

Ali Hortaçsu, F Martínez-Jerez, and Jason Douglas. The geography of trade in online transactions: Evidence from ebay and mercadolibre. *American Economic Journal: Microeconomics*, 1(1):53–74, 2009.

David Hummels and Alexandre Skiba. Shipping the good apples out? an empirical confirmation of the alchian-allen conjecture. *Journal of Political Economy*, 112(6):1384–1402, 2004.

Robert Jensen. The digital provide: Information (technology), market performance, and welfare in the south indian fisheries sector. *The Quarterly Journal of Economics*, 122(3):879–924, 2007.

Daniel Kaufmann, Aart Kraay, and Massimo Mastruzzi. The worldwide governance indicators: methodology and analytical issues. *Hague Journal on The Rule of Law*, 3(2):220–246, 2011.

Amit Khandelwal. The long and short (of) quality ladders. *The Review of Economic Studies*, 77(4):1450–1476, 2010.

Theresa Kuchler and Johannes Stroebel. Social finance. Technical report, National Bureau of Economic Research, 2020.

Theresa Kuchler, Yan Li, Lin Peng, Johannes Stroebel, and Dexin Zhou. Social proximity to capital: Implications for investors and firms. Technical report, National Bureau of Economic Research, 2020a.

Theresa Kuchler, Dominic Russel, and Johannes Stroebel. The geographic spread of covid-19 correlates with structure of social networks as measured by facebook. Technical report, National Bureau of Economic Research, 2020b.

Edward E Leamer and James Levinsohn. International trade theory: the evidence. *Handbook of International Economics*, 3:1339–1394, 1995.

Andrei A Levchenko. Institutional quality and international trade. *The Review of Economic Studies*, 74(3): 791–819, 2007.

Staffan Burenstam Linder. *An essay on trade and transformation*. Almqvist & Wiksell Stockholm, 1961.

John McCallum. National borders matter: Canada-us regional trade patterns. *American Economic Review*, 85(3):615–623, 1995.

Marc J Melitz. The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6):1695–1725, 2003.

Marc J Melitz and Gianmarco IP Ottaviano. Market size, trade, and productivity. *The Review of Economic Studies*, 75(1):295–316, 2008.

Nathan Nunn. Relationship-specificity, incomplete contracts, and the pattern of trade. *The Quarterly Journal of Economics*, 122(2):569–600, 2007.

Maurice Obstfeld and Kenneth Rogoff. The six major puzzles in international macroeconomics: is there a common cause? *NBER Macroeconomics Annual*, 15:339–390, 2000.

Trevor J Pemberton, Michael DeGiorgio, and Noah A Rosenberg. Population structure in a comprehensive genomic data set on human microsatellite variation. *G3: Genes, Genomes, Genetics*, 3(5):891–907, 2013.

Monika Piazzesi, Martin Schneider, and Johannes Stroebel. Segmented housing search. Technical report, 2015.

Priya Ranjan and Jae Young Lee. Contract enforcement and international trade. *Economics & Politics*, 19 (2):191–218, 2007.

James E Rauch. Networks versus markets in international trade. *Journal of International Economics*, 48(1): 7–35, 1999.

James E Rauch. Business and social networks in international trade. *Journal of Economic Literature*, 39(4): 1177–1203, 2001.

James E Rauch and Vitor Trindade. Ethnic chinese networks in international trade. *Review of Economics and Statistics*, 84(1):116–130, 2002.

Oliver Rehbein, Simon Rother, et al. Distance in bank lending: The role of social networks. Technical report, University of Bonn and University of Mannheim, Germany, 2020.

J. M. C. Santos Silva and Silvana Tenreyro. The log of gravity. *Review of Economics and Statistics*, 88(4): 641–658, 2006.

Peter K Schott. Across-product versus within-product specialization in international trade. *The Quarterly Journal of Economics*, 119(2):647–678, 2004.

Ina Simonovska and Michael E Waugh. The elasticity of trade: Estimates and evidence. *Journal of International Economics*, 92(1):34–50, 2014.

Enrico Spolaore and Romain Wacziarg. Ancestry, language and culture. In *The Palgrave Handbook of Economics and Language*, pages 174–211. Springer, 2016.

Enrico Spolaore and Romain Wacziarg. Ancestry and development: New evidence. *Journal of Applied Econometrics*, 33(5):748–762, 2018.

Meredith Startz. The value of face-to-face: Search and contracting problems in nigerian trade. *Working Paper*, 2016.

Claudia Steinwender. Real effects of information frictions: When the states and the kingdom became united. *American Economic Review*, 108(3):657–96, 2018.

Shawn W Tan. The geography of trade in the european single market. 2016.

Marcel P Timmer, Erik Dietzenbacher, Bart Los, Robert Stehrer, and Gaaitzen J De Vries. An illustrated user guide to the world input–output database: the case of global automotive production. *Review of International Economics*, 23(3):575–605, 2015.

Jan J Tinbergen. Shaping the world economy; suggestions for an international economic policy. 1962.

Daniel Trefler. The case of the missing trade and other mysteries. *The American Economic Review*, pages 1029–1046, 1995.

Don Wagner, Keith Head, and John Ries. Immigration and the trade of provinces. *Scottish Journal of Political Economy*, 49(5):507–525, 2002.

Riley Wilson. The impact of social networks on eitc claiming behavior. 2019.

Appendix for "International Trade and Social Connectedness"

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A The Determinants of International Social Connectedness

In Section A.1, we explore a number of further case studies of the social connectedness of individual countries. In Section A.2, we formally analyze the role of geography and other factors such as similarity of language, history, religion, and economic development in shaping international social connections.

A.1 Case Studies of International Social Connectedness

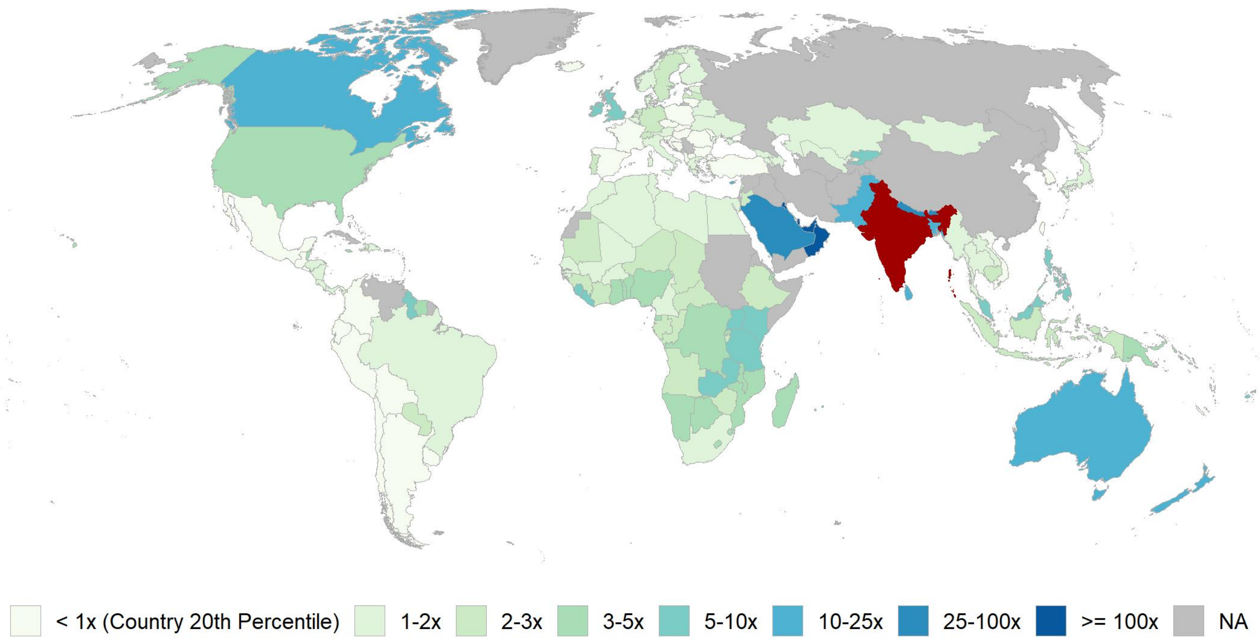
Figures A.1 to A.5 present heat maps of the social connections of several countries in addition to the heat map of Portugal's international connections in Panel A of Figure 1. As before, darker colors correspond to closer connections.

India and Malaysia. Figure A.1 shows the social connectedness of two Asian countries, India (Panel A) and Malaysia (Panel B). Both countries are strongly connected to the countries on the Arab peninsula, likely a result of migrant workers from India and Malaysia moving to work in these countries in recent years. Similarly, Malaysia is strongly connected to Nepal, likely due to a guest worker program allowing Nepalis to work in Malaysia. Social connections also appear to reflect earlier episodes of migrant and forced labor movements. For instance, India is strongly connected to Guyana in South America. In the 19th century, there was a lack of plantation workers following the abolition of slavery in this former European colony. Indians were selected to fill the gap as they were used to working under tropical conditions and willing to accept cheap terms (Davis, 1951), and the resulting social connections to India appear to remain a century later. Finally, the Muslim-majority Malaysia is more strongly connected to the predominantly Muslim countries on the Indian subcontinent (Pakistan, Bangladesh, and the Maldives) than it is connected to India itself, suggesting a role of religion in shaping today's social connections.

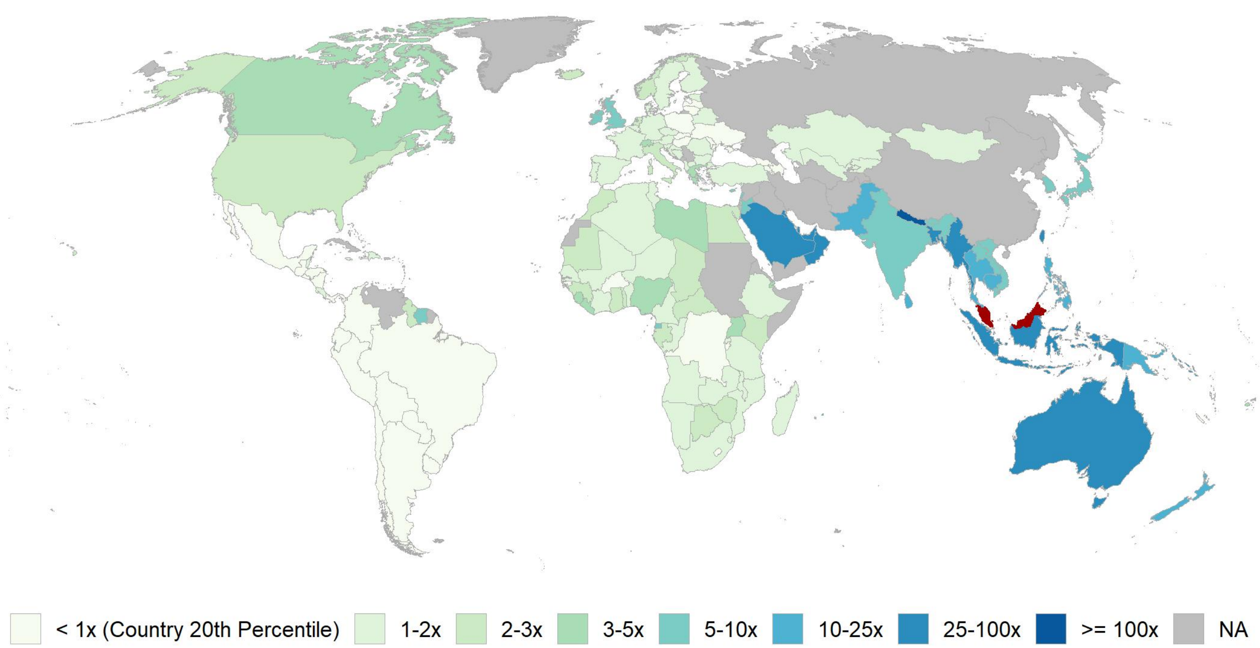
Argentina. Figure A.2 shows the social connectedness of Argentina. Argentina is strongly connected to all Spanish-speaking countries in Latin America. Connections to Portuguese-speaking Brazil are substantially weaker, even though the two countries are geographically close and share a common border. Similarly, Argentina's strongest connection in Europe is to Spain. It is much less connected to Italy, despite the fact that Italians were the largest group of post-colonial immigrants (more than from Spain) and 60% of Argentinians have some Italian ancestry. These findings suggest an important role of shared language for today's connections.

Figure A.1: Social Connectedness of India and Malaysia

(A) Social Connectedness of India



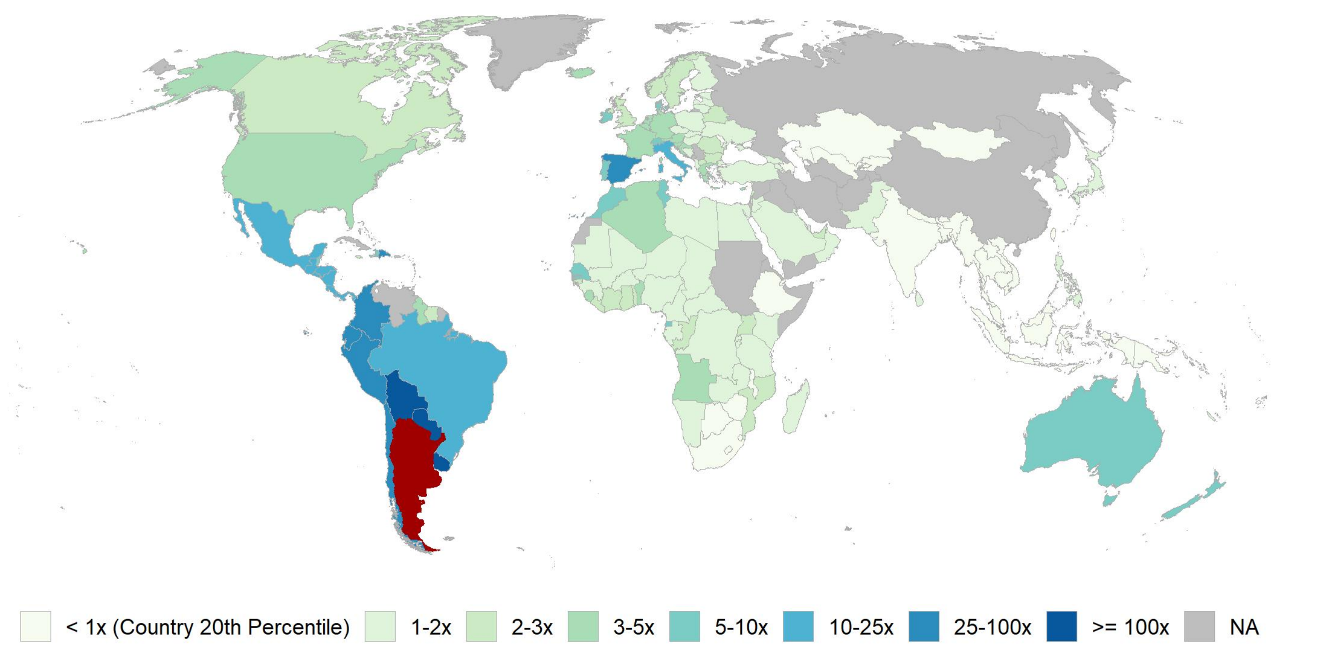
(B) Social Connectedness of Malaysia



Note: Figures show a heat map of the social connectedness of India (Panel A) and Malaysia (Panel B). For each country in our data, the colors highlight connections to the focal country, given in red. The lightest color corresponds to the 20th percentile of the connectedness to the focal country; darker colors correspond to closer connections.

Figure A.2: Social Connectedness of Argentina

(A) Social Connectedness of Argentina



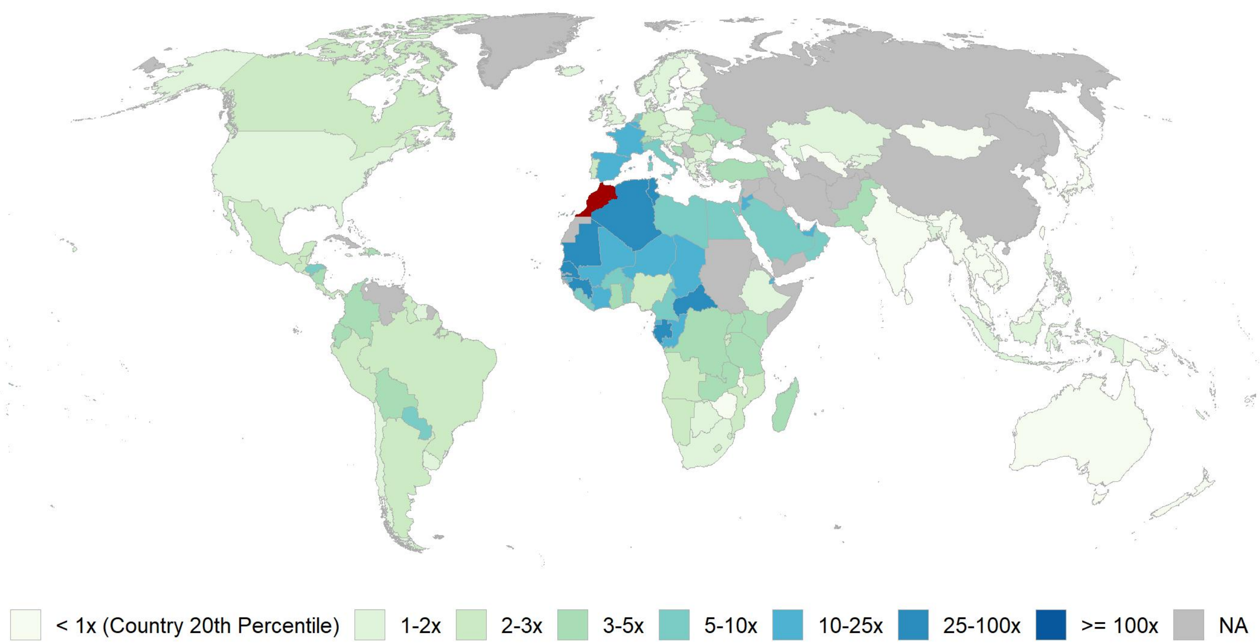
Note: Figure shows a heat map of the social connectedness of Argentina. For each country in the world, the colors highlight connections to the focal country, given in red. The lightest color corresponds to the 20th percentile of the connectedness to the focal country; darker colors correspond to closer connections.

Morocco and Mauritania. Figure A.3 shows the social connectedness of two neighboring countries in Northwest Africa, Morocco (Panel A) and Mauritania (Panel B). Both Morocco and Mauritania are former French colonies and, as such, still have strong social ties to France. The populations of both countries are predominantly Muslim, which helps to explain their strong ties to other Muslim countries in Northern Africa and the Middle East. On the other hand, Mauritania has much stronger ties to Sub-Saharan Africa than Morocco does. This is likely related to the fact that Morocco's population is almost entirely Arab-Berber, while Mauritania has a substantial population of Haratin and West African ethnicity. These patterns suggest that ethnic ties are important in shaping friendships across countries.

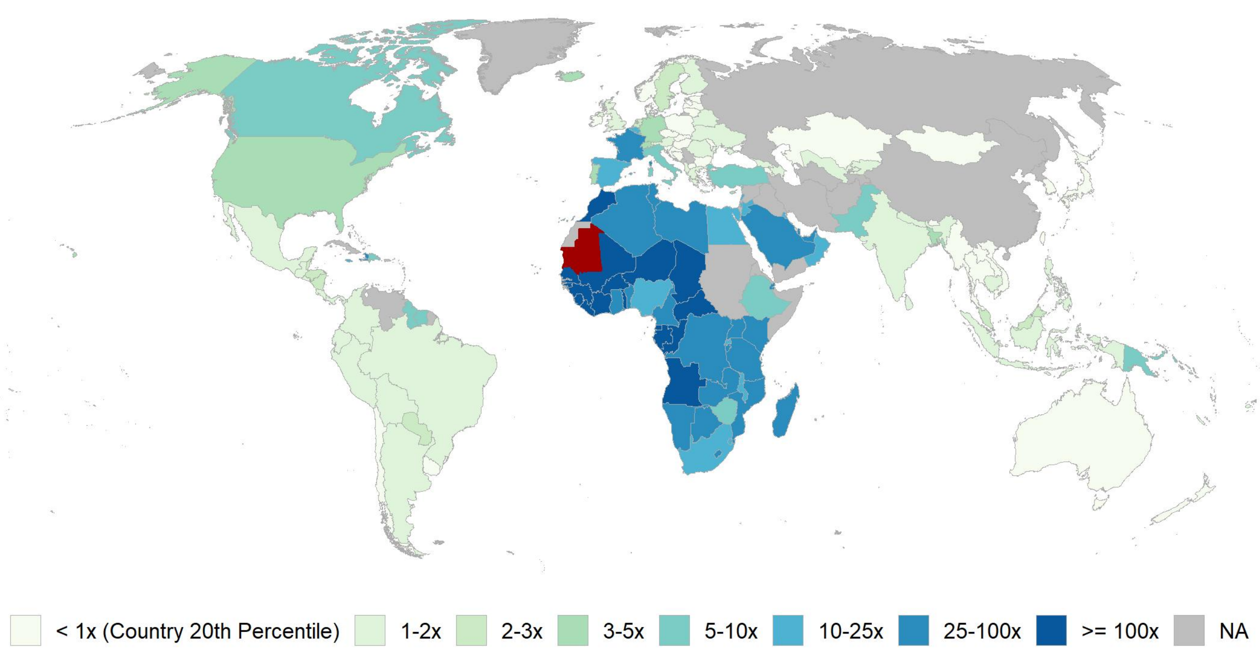
Azerbaijan and Turkey. Figure A.4 shows the social connectedness of Azerbaijan (Panel A) and Turkey (Panel B), two countries in Northwest Asia that share a short border. Both are strongly connected to each other, the nearby Caucasus countries of Armenia and Georgia, and Central European countries which have welcomed migrants from the two nations. However, Azerbaijan, a former Soviet Republic, is much more connected with countries in Europe and Central Asia that were also part of the Soviet Union, including Russia, Kazakhstan, Uzbekistan, Ukraine, Belarus, Lithuania, Latvia, and Estonia. Turkey, whose residents are predominately Muslim, is more connected to other predominately Muslim countries including Afghanistan, Syria, Lebanon, Iraq, Saudi Arabia, Yemen, and Libya. These patterns emphasize that historical ties and religion play important roles in shaping today's social connections.

Figure A.3: Social Connectedness of Morocco and Mauritania

(A) Social Connectedness of Morocco



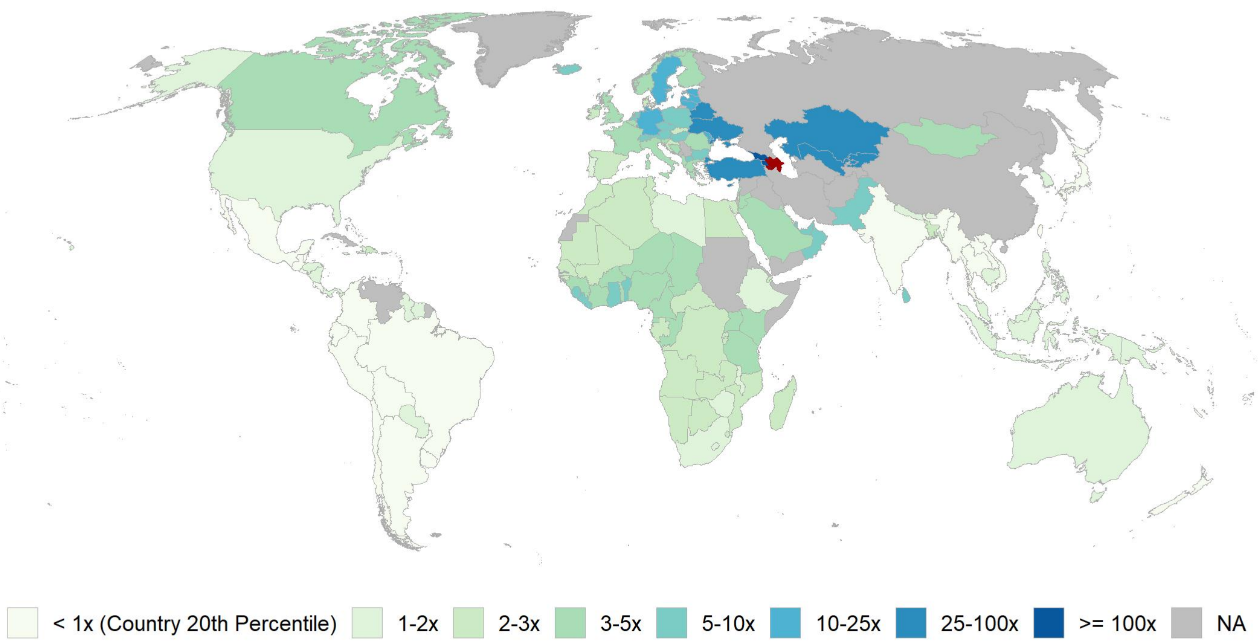
(B) Social Connectedness of Mauritania



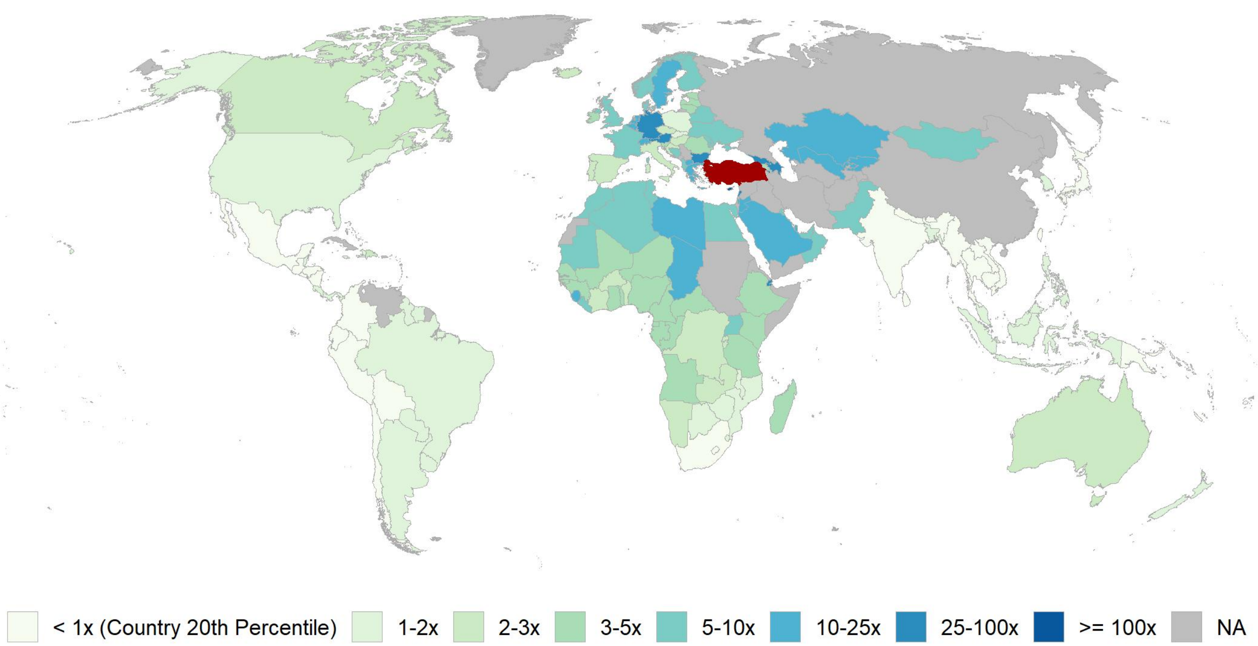
Note: Figures show a heat map of the social connectedness of Morocco (Panel A) and Mauritania (Panel B). For each country in the world, the colors highlight connections to the focal country, given in red. The lightest color corresponds to the 20th percentile of the connectedness to the focal country; darker colors correspond to closer connections.

Figure A.4: Social Connectedness of Azerbaijan and Turkey

(A) Social Connectedness of Azerbaijan



(B) Social Connectedness of Turkey

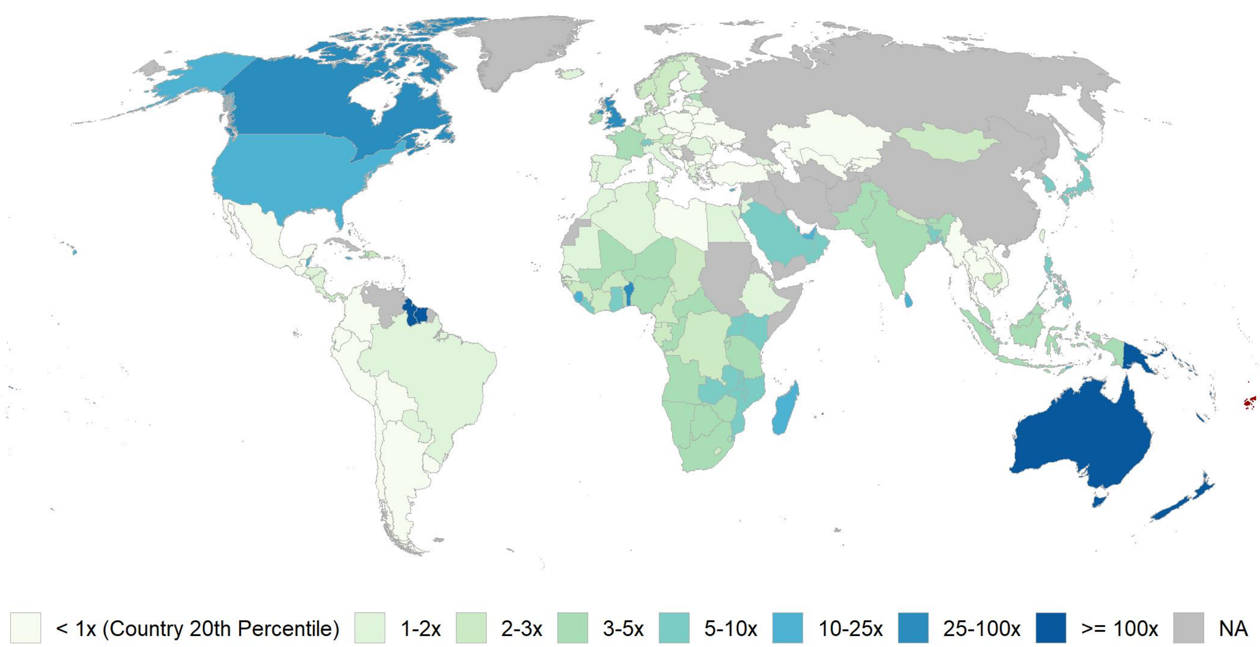


Note: Figures show a heat map of the social connectedness of Azerbaijan (Panel A) and Turkey (Panel B). For each country in the world, the colors highlight connections to the focal country, given in red. The lightest color corresponds to the 20th percentile of the connectedness to the focal country; darker colors correspond to closer connections.

Fiji. Panel B of Figure A.5 shows the social connectedness of Fiji. Fiji, a former British colony, is strongly connected to other countries that were part of the British empire in Oceania (Australia, New Zealand, Papua New Guinea, and the Solomon Islands), as well as other English-speaking nations, including Canada, the United States, the United Kingdom, and Guyana. The country's connections to Guyana and Suriname are particularly strong compared to its connections with countries throughout the rest of South America. A potential explanation for this lies in the Indian worker program described previously. Between 1830 and 1930, over a million indentured laborers from India were relocated to European colonies, including Dutch Suriname and British Fiji and Guyana. These patterns suggest that ties from migratory movements significantly impact international connectedness.

Figure A.5: Social Connectedness of Fiji

(A) Social Connectedness of Fiji



Note: Figure shows a heat map of the social connectedness of Fiji. For each country in the world, the colors highlight connections to the focal country, given in red. The lightest color corresponds to the 20th percentile of the connectedness to the focal country; darker colors correspond to closer connections.

A.2 Regression Analysis

The case studies above suggest that several factors such as geographic distance, colonial history, and past migration shape today's social connections between countries. We next estimate the following regression to analyze the contributions of these factors to social connectedness more systematically:

$$\log(SCI_{i,j}) = \beta + \gamma G_{i,j} + \delta_i + \delta_j + \epsilon_{i,j}. \tag{A.1}$$

The dependent variable is the logarithm of the *Social Connectedness Index* between country i and country j. The vector $G_{i,j}$ captures variables that might explain international social connectedness. We also include fixed effects for each country, δ_i and δ_j, to absorb any country-specific factors that may affect our measure of a country's connections to others, such as patterns of Facebook usage or internet penetration.

A.2.1 Geography and Social Connectedness

We first explore the role of geographic proximity in shaping international social connectedness. We measure the geographic distance between two countries as the population-weighted distance given by CEPII; summary statistics are presented in Table A.1. The binscatter plots in Figure A.6 show a broadly log-linear relationship between distance and social connectedness, both with and without country fixed effects. For large distances, the relationship becomes slightly convex, indicating that distance matters somewhat less once countries are already far apart.

Table A.1: Summary Statistics and Data Sources

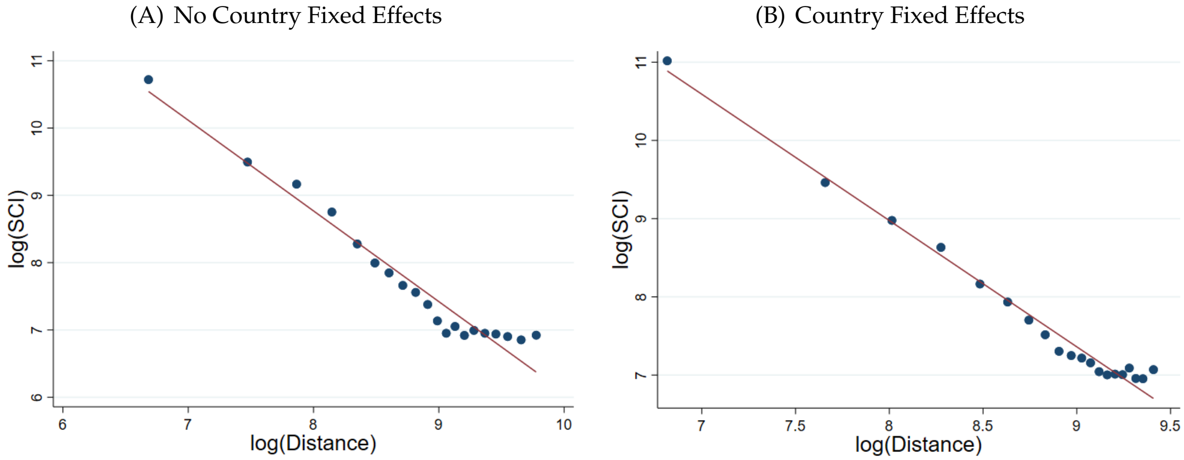
	Mean	P10	P25	P50	P75	P90	N	Source
log(SCI)	7.72	5.83	6.44	7.37	8.66	10.13	28,730	Facebook
log(Distance)	8.78	7.69	8.43	8.95	9.32	9.60	28,730	CEPII
log(1+Migrant Population)	2.44	0.00	0.00	0.00	4.81	8.02	28,392	United Nations
Common Colonizer	0.11	0.00	0.00	0.00	0.00	1.00	28,730	CEPII
Colonial Relationship	0.01	0.00	0.00	0.00	0.00	0.00	28,730	CEPII
Genetic Distance	0.04	0.01	0.02	0.04	0.05	0.06	24,806	Spolaore et al. (2018)
Common Official Language	0.16	0.00	0.00	0.00	0.00	1.00	28,730	CEPII
Religious Distance	0.75	0.54	0.66	0.80	0.86	0.96	25,760	Spolaore et al. (2016)
Δ GDP per Capita (in '00,000$s)	0.19	0.01	0.03	0.10	0.28	0.51	28,730	CEPII
Common Border	0.02	0.00	0.00	0.00	0.00	0.00	28,730	CEPII
Same Continent	0.22	0.00	0.00	0.00	0.00	1.00	28,730	UNStats
Same Subcontinent	0.12	0.00	0.00	0.00	0.00	1.00	28,730	UNStats

Note: Table presents summary statistics of variables used in Appendix A. Variables include the logarithm of SCI, the logarithm of distance, the logarithm of 1 plus the average migrant population, a dummy indicating whether the pair of countries had a common colonizer post-1945, a dummy indicating whether the pair of countries was in a colonial relationship post-1945, genetic distance following Spolaore and Wacziarg (2018), a common official language dummy, religious distance following Spolaore and Wacziarg (2016), differences in GDP per capita (in hundred thousands of dollars), a common border dummy, a same continent dummy, and a same subcontinent dummy.

Table A.2 explores the role of distance using regression A.1. Column 1 includes only fixed effects for country i and country j. The results suggest that about 30% of the pairwise connectedness of countries is explained by the fact that countries differ in their *average* degree of global connectedness. In other words, most of the cross-sectional variation in social connectedness across country pairs is the result of characteristics that vary at the country pair level, and not characteristics that vary at the country level.

Column 2 adds $\log(Distance_{i,j})$ as a control to the country fixed effects; this specification corresponds to the binscatter plots in Panel B of Figure A.6. The estimates imply that a 10% increase in the geographic distance between countries is associated with a 16.2% decline in social connectedness. In terms of magnitude, this elasticity is similar to the elasticity of connectedness to geographic distance

Figure A.6: Social Connectedness vs. Geographic Distance



Note: Figures show binscatter plots of social connectedness and geographic distance. Panel A regresses log(SCI) on log(Distance) without any fixed effects, while Panel B controls for country fixed effects.

between U.S. counties in Bailey et al. (2018a). Moreover, geographic distance explains more than one half of the variation in social connectedness across countries after accounting for country fixed effects.

Column 3 explores the importance of potential non-linearities in the relationship between geographic distance and social connectedness. Specifically, instead of controlling for $\log(Distance_{i,j})$ linearly, we include dummy variables for percentiles of $\log(Distance_{i,j})$. The R^2 of the regression is only slightly higher—67.5% instead of 66.6%– when we control for these percentiles. This finding confirms that the baseline log-linear specification is reasonable. Nevertheless, in columns 4 and 5 of Table A.2, we split the sample into country pairs that are more or less than 6,000km apart. The estimated elasticity is -1.89 for countries less than 6,000km apart, and -0.90 for countries more than 6,000km apart.

Column 6 of Table A.2 explores whether sharing a border increases social connectedness beyond geographic distance. For instance, a direct border may make it more likely that residents frequently spend time in the other country, either for work or leisure. It might also induce governments to cooperate and establish policies fostering cross-country interactions. Consistent with these hypotheses, the estimates indicate that citizens of two countries that share a border are about twice as likely to be friends with each other compared with citizens of two countries that are equally far apart but that do not share a border. However, the incremental R^2 of including this additional control over distance alone is relatively small at 0.2%, since the common border indicator does not allow us to understand the substantial variation in connectedness between the vast majority of pairs of non-neighboring countries.

We also examine how continental borders shape friendships between countries. Following UNStats, we group countries into five continents—Africa, the Americas, Asia, Europe, and Oceania—and into subcontinents such as Northern Africa and Sub-Saharan Africa. The regression results in column 7 of Table A.2 show that countries on the same subcontinent are about twice as connected as two countries that are equally far apart but on different continents, all else equal. Being on the same continent (but not the same subcontinent) is associated with a 76% increase in social connectedness relative to two countries that are equally far apart but on different continents. Column 8 explores whether sharing

Table A.2: The Geographic Determinants of Social Connectedness

	Dependent variable: log(SCI)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Distance)		-1.615***	100	-1.887***	-0.899***	-1.562***	-1.092***	-1.201***
		(0.038)	Quantiles	(0.060)	(0.076)	(0.039)	(0.059)	(0.052)
Common border						0.755***	0.860***	0.858***
						(0.112)	(0.115)	(0.107)
Same continent							0.760***	
							(0.087)	
Same subcontinent							0.406***	
							(0.116)	
Both in Africa								1.522***
								(0.159)
Both in Americas								0.114
								(0.114)
Both in Asia								0.395***
								(0.111)
Both in Europe								0.779***
								(0.168)
Both in Oceania								2.668***
								(0.327)
Orig. and Dest. Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Sample	All	All	All	< 6000km	> 6000km	All	All	All
R^2	0.303	0.666	0.675	0.662	0.552	0.668	0.693	0.706
N	28,730	28,730	28,730	10,594	18,136	28,730	28,730	28,730

Note: Table shows results of regression A.1. The dependent variable is the logarithm of social connectedness for a country pair. Explanatory variables include the logarithm of distance, a dummy indicating a common border, a same continent dummy, a same subcontinent dummy, and dummies indicating whether the pair of countries belongs to Africa, the Americas, Asia, Europe or the Oceania region. In column 3, the logarithm of distance is replaced by indicators based on 100 quantiles of distance. All specifications include fixed effects for the origin and destination country. Standard errors are clustered by origin and destination country. We have data on social connectedness for 170 countries, which leads to 28,730 (= 170 x 169) observations. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

a continent affects friendships differently on different continents. Countries in Oceania and Africa are substantially more likely to be socially connected to other countries on the same continent than predicted purely by geographic distance. On the other hand, countries in the Americas are not significantly more likely to be connected to each other than to countries on a different continent that are equally far away.

A.2.2 Social Connectedness and Country Similarity

The previous results highlight that various measures of geographic proximity can explain a little over half of the variation in social connectedness across country pairs that is not explained by country fixed effects. We next explore the role of other factors in explaining international friendship linkages. Specifically, we analyze the role of past migration, colonial history, genetic similarity, common language, religion, and similarity in GDP. Table A.1 shows summary statistics on these variables, as well as the data sources; not all variables are available for all country pairs. Table A.3 presents the cross-correlation of these gravity variables with the SCI and with each other. Naturally, many of the variables are somewhat correlated with one another: for example, countries that share a colonial history are more likely to have a common official language. Table A.4 contains the results from Regression A.1 when controlling for these variables. We first explore the relationships between the gravity variables and social connectedness separately for each variable, before analyzing them jointly in a multivariate analysis.

Table A.3: Correlation Table: Social Connectedness and Determinants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) log(SCI)	1.00											
(2) log(Distance)	-0.60	1.00										
(3) log(1+Migrant Population)	0.38	-0.42	1.00									
(4) Common Colonizer	0.28	-0.03	-0.06	1.00								
(5) Colonial Relationship	0.10	-0.01	0.16	-0.03	1.00							
(6) Genetic Distance	-0.42	0.57	-0.44	0.01	0.00	1.00						
(7) Common Official Language	0.45	-0.10	0.11	0.39	0.14	-0.01	1.00					
(8) Religious Distance	-0.27	0.19	-0.17	0.03	0.00	0.08	-0.22	1.00				
(9) Δ GDP per Capita (in '00,000$s)	0.03	0.01	0.31	-0.11	0.06	-0.11	-0.02	-0.03	1.00			
(10) Common Border	0.27	-0.36	0.27	0.06	-0.00	-0.16	0.12	-0.12	-0.07	1.00		
(11) Same Continent	0.55	-0.65	0.25	0.10	-0.03	-0.39	0.18	-0.17	-0.15	0.23	1.00	
(12) Same Subcontinent	0.53	-0.52	0.12	0.12	-0.02	-0.25	0.27	-0.18	-0.22	0.28	0.71	1.00

Note: Table presents correlations between variables used in Section A. Variables include the logarithm of SCI, the logarithm of distance, the logarithm of 1 plus the average migrant population, a dummy indicating whether the two countries had a common colonizer post 1945, a dummy indicating whether the pair of countries was in a colonial relationship post 1945, genetic distance, a common official language dummy, religious distance, differences in GDP per capita (in hundred thousands of dollars), a common border dummy, a same continent dummy and a same subcontinent dummy.

Migration. It is likely that migrants retain many friends and family ties to their countries of origin. As a result, we would expect that past migration patterns explain some of the observed cross-sectional variation in social connectedness. To measure migration between country pairs, we use bilateral migration data from the Population Division of the Department of Economic and Social Affairs of the United Nations.[1] The estimates in column 1 of Table A.4 show a strong relationship between past migration and current social relationships. Doubling the average migrant population increases social connectedness between countries by over 20%. Including migration in addition to distance and country fixed effects increases the R^2 of the regression by 6.1 percentage points.

Common Colonial History. The case studies in Appendix A.1 suggest that countries with a common colonial history maintain closer present-day social ties. To systematically explore this relationship, we

[1]Most of the data are based on population censuses from the year 2015. Population registers and surveys are used to supplement the census data. Whenever the number of migrants from a country to another country is missing, we set the number to zero. For each country pair, we then compute the average of the number of migrants from country A living in country B and the number of migrants from country B living in country A. To deal with zero migration between two countries, we add one before taking the logarithm. Dividing this number by the sum of the populations in countries A and B leaves the coefficient almost unchanged, because of the log-log specification and the country-level fixed effects.

Table A.4: The Determinants of Social Connectedness

	Dependent variable: log(SCI)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(Distance)	-1.172***	-1.566***	-1.235***	-1.482***	-1.539***	-1.583***	-0.612***
	(0.0418)	(0.0341)	(0.0368)	(0.0410)	(0.0418)	(0.0366)	(0.0492)
log(1+Migrant Population)	0.218***						0.172***
	(0.0117)						(0.0110)
Common Colonizer		1.093***					0.431***
		(0.0862)					(0.0614)
In Colonial Relationship		1.959***					1.057***
		(0.226)					(0.149)
Genetic Distance			-32.57***				-22.87***
			(1.864)				(1.662)
Common Official Language				1.210***			0.643***
				(0.0770)			(0.0614)
Religious Distance					-1.549***		-0.542***
					(0.174)		(0.124)
Δ GDP per Capita (in '00,000$s)						-1.305***	-0.941***
						(0.284)	(0.211)
Common Border							0.0301
							(0.101)
Same Sontinent							0.594***
							(0.0667)
Same Subcontinent							-0.104
							(0.0871)
Orig. and Dest. Country FE	Y	Y	Y	Y	Y	Y	Y
Coeff. on distance w/o regressors	-1.614	-1.615	-1.616	-1.615	-1.610	-1.615	-1.608
R^2	0.722	0.694	0.714	0.705	0.671	0.669	0.807
Incremental R^2 of regressors	0.061	0.032	0.049	0.044	0.009	0.007	0.141
N	28,392	28,730	24,806	28,730	25,760	28,730	23,562

Note: Table shows results of regression A.1. The dependent variable is the logarithm of the social connectedness for a country pair. Independent variables include the logarithm of distance, the logarithm of 1 plus the average migrant population, a dummy indicating whether the pair of countries had a common colonizer post-1945, a dummy indicating whether the pair of countries was in a colonial relationship post-1945, genetic distance, a common official language dummy, religious distance, differences in GDP per capita (in hundred thousands of dollars), a common border dummy, a same continent dummy and a same subcontinent dummy. All specifications include fixed effects for the origin and destination country. Standard errors are clustered by origin and destination country. We have data on social connectedness for 170 countries, which leads to 28,730 (= 170 x 169) observations. Not all variables are available for all country pairs. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

use two measures of colonial history. Our first measures is an indicator for having a common colonizer after 1945. The second measure is an indicator for having been in a colonial relationship post 1945. The estimates in column 2 indicate that colonial history correlates strongly with social connectedness. Countries with a common colonizer have almost twice as many friendship links on Facebook as other countries that are similarly far apart. Having been in a colonial relationship increases the connectedness between countries by a factor close to three. Adding controls for colonial ties to distance and country fixed effects explains an additional 3.2% of the cross-sectional variation in social connectedness.

Genetic Distance. Homophily suggests that there are likely to be more connections among countries whose populations are more similar to each other, including along genetic lines. We measure genetic distance following Spolaore and Wacziarg (2018).[2] Table A.3 shows that genetic distance has a raw correlation of −42% with social connectedness; this is reflected in the strong negative relationship in the regression analysis. Going from the 10th percentile of genetic distance to the 90th percentile is associated with a decrease in social connectedness of 162%. Including genetic distance leads to an incremental increase in explanatory power, as measured by the R^2, of just under 5%.

Common Language. Language is a natural determinant of social relationships. After all, it is hard to form a personal relationship without speaking the same language. To formally explore the relationship between language and social connectedness, we use an indicator variable for whether two countries share a common official language. The common language indicator is strongly correlated with social connections as evidenced by a raw correlation of 45% presented in Table A.3. Column 4 of Table A.4 confirms the strong relationship. Having a common language more than doubles the social connectedness between two countries, and increases the R^2 by 4.4 percentage points.

Similar Religion. People of the same or similar religion may find it easier to connect to others who share their belief system. In addition, people of the same religion may be more likely to meet each other across countries, for instance when traveling for pilgrimage. To explore the effect of religion on social connectedness, we measure religious distance between countries following Spolaore and Wacziarg (2016).[3] The estimates in column 5 of Table A.4 suggest that social connections decrease by 65% when moving from the 10th percentile to the 90th percentile of religious distance. The incremental R^2 of religion is less than 1%, which is less than the variation explained by the other variables explored so far.

Similarity in GDP. Bailey, Cao, Kuchler, Stroebel, and Wong (2018a) show that, at the individual level, people are more likely to be friends with others of similar incomes. We next explore whether this is also true for international social connectedness. For each country pair, we compute the absolute difference in GDP per capita. Column 6 of Table A.4 shows that differences in GDP correlate with social connectedness. A ten thousand dollar higher absolute difference in GDP per capita across two countries corresponds to a 13.1% decline in social connectedness. However, differences in GDP only explain a small fraction of the cross-sectional variation in social connections, with an incremental R^2 of only 0.7%.

[2] This measure of genetic distance is based on variation in the human DNA for ethnic groups from Pemberton, DeGiorgio, and Rosenberg (2013) and converted to a country-to-country measure using the shares of each ethnic group in each country's populations from Alesina, Devleeschauwer, Easterly, Kurlat, and Wacziarg (2003). It is therefore the expected genetic distance between two individuals randomly selected from the two countries.

[3] This measure of religious distance between any two countries is based on two components: the distance between different religions and the share of the population in a country that follow a religion. The proximity of two religions is based on how many nodes the two religions share in a tree describing the relationship between different religions. For instance, Roman Catholics are more closely related to Orthodox Christians than to Muslims. The religious distance between two countries is then obtained by summing across the distances of all religions while weighting each religion by the fraction of people in the two countries that follow the religion.

Multivariate Regression. The first six columns of Table A.4 have shown the relationship between each regressor and social connectedness separately (in addition to controls for distance and country fixed effects). However, many of these variables are correlated with each other, as shown in Table A.3, and they often capture related aspects of across-country similarity. Column 7 explores how much of the variation in social connectedness can be jointly explained by these variables. As expected, the estimated coefficients for most variables decrease somewhat, though almost all variables retain their economic and statistical significance. The estimated effect of distance drops to about one third of the coefficient in the univariate regressions, suggesting that distance captures some aspects of the other cultural and social similarity in explaining social connectedness. Taken together, the incremental R^2 of all additional regressors (beyond distance and fixed effects) is 14.1%.

Table A.5: Incremental Explanatory Power of Regressors for SCI

Incremental R^2	Dependent variable: log(SCI)
log(Distance)	1.85
log(1+Migrant Population)	3.24
Common Colonizer	0.33
Colonial Relationship	0.20
Genetic Distance	2.16
Common Official Language	1.00
Religious Distance	0.10
Δ GDP per Capita (in '00,000$s)	0.33
Common Border	0.00
Same Continent	0.69
Same Subcontinent	0.01

Note: Table reports the incremental R^2 of each regressor when included/excluded in a regression of the logarithm of SCI on the full panel of regressors. This is alike the specification in column 7 of Table A.4. To get the incremental R^2, we compute the difference between the R^2 of a regression when we exclude the variable from the set of explanatory variables and the R^2 when we include the variable in the set of explanatory variables. For each variable considered, we run both regressions on the same set of observations.

As shown in Table A.3, a number of the control variables in Table A.4 are highly correlated. For example, the correlation between genetic distance and our measure of migration is -0.44. Therefore, another interesting metric is how much explanatory power each variable contributes when controlling for all other variables. For each variable, we run two regressions with the specification in column 7 of Table A.4: one where we exclude the variable of interest and one where we include it. We then compare the R^2 of the two regressions, giving us an estimate of the incremental explanatory power of the variable beyond all other explanatory variables. The results of this exercise are reported in Table A.5. We find that migration has the largest incremental R^2 with 3.24% followed by genetic distance with 2.16%. Geographic distance (1.85%) and the common official language dummy (1.00%) also add sizable explanatory power. Colonial heritage, religious distance, a common border, and being on the same subcontinent have very little explanatory power once we control for other factors.

B Trade and Social Connectedness

In this appendix, we present material complementary to our analysis of country-level trade in Section 2. Appendix B.1 explains the construction of the data, Appendix B.2 shows robustness to using OLS estimations instead of PPML, Appendix B.3 estimates time-varying elasticities of trade to social connections, and Appendix B.4 runs a horse race between different gravity variables in explaining international trade. Appendix B.5 studies the effects of social clusters on trade.

B.1 Construction of Trade and SCI Data

For the analyses in Section 2, we merge data on international social connectedness with product-level trade data from CEPII. Of the 170 countries for which we have data on international social connectedness and gravity variables, five countries are not included in the trade data. These countries are Botswana, Lesotho, Luxembourg, Namibia, and Swaziland. In the original data, products are classified according to the 6-digit HS96 classification into 4,914 product categories. In order to construct total bilateral trade, used in Section 2, we aggregate trade across all products for each exporter-importer pair. We replace missing trade values with zero trade values. The final data that contains information on social connectedness, gravity variables, and aggregate bilateral trade include 165 countries and 27,060 (= 165 x 164) observations. In Section 2, we also use data on product-level trade instead of total trade. For computational reasons, we aggregate trade flows up to the first two digits of the HS96 product code for each exporter-importer pair. The first two digits of the product code are referred to as the "HS chapter". For example, chapter 09 includes "Coffee, Tea, Maté and Spices." This procedure results in 96 product categories. We replace missing trade values with zeros. The panel on product-level trade and social connectedness contains 2,597,760 (=165 x 164 x 96) observations.

B.2 Gravity Regressions (OLS) - Intensive Margin of Trade

Table 2 in Section 2 showed results from regressing aggregate bilateral trade on social connectedness and other gravity variables. The regression was estimated using Poisson Pseudo Maximum Likelihood (PPML) to account for zero bilateral trade between countries. Here, we show that the results are robust to estimating the relationships using OLS. We focus on the intensive margin of trade in order to avoid problems with zero-trade observations. We estimate the following regression:

$$log(X_{i,j}) = \beta + \gamma G_{i,j} + \delta_i + \delta_j + \epsilon_{i,j} \tag{B.1}$$

The dependent variable $log(X_{i,j})$ denotes the logarithm of the total value of exports from country i to country j. The results are reported in Table B.1. As before, social connectedness explains a substantial part of the variation in bilateral trade at the intensive margin. Column 2 shows that social connectedness explains 29.5% of the within variation of trade after controlling for exporter and importer fixed effects, nearly as high as the within-R^2 of 30.4% for distance (see column 3). Similarly to Table 1, column 4 shows that gravity variables together explain a much smaller share of variation—here, less than half as much—than social connectedness. Column 7 shows that, after controlling for distance and other gravity variables, the coefficient on social connectedness is similar to that obtained using PPML (0.37 vs. 0.28). Overall, these results show that our baseline results are not an artefact of the specific estimation method.

Table B.1: Gravity Regressions (OLS) - Intensive Margin of Trade - 2017

	Dependent variable: log(Aggregate Bilateral Trade)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(SCI)		0.773***			0.428***		0.368***	0.374***
		(0.0272)			(0.0318)		(0.0326)	(0.0332)
log(Distance)			-1.711***		-1.026***	-1.547***	-1.026***	
			(0.0650)		(0.0756)	(0.0657)	(0.0770)	
Common Border				3.671***		0.844***	0.692***	0.621***
				(0.237)		(0.202)	(0.188)	(0.204)
Common Official Language				1.258***		0.555***	0.194**	0.209**
				(0.153)		(0.0903)	(0.0818)	(0.0829)
Common Colonizer				0.902***		0.687***	0.362***	0.352***
				(0.190)		(0.143)	(0.119)	(0.117)
Colonial Relationship				0.591**		1.158***	0.645***	0.645***
				(0.269)		(0.184)	(0.146)	(0.146)
Orig. and Dest. Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Distance Control Groups								Y
N	18,393	18,393	18,393	18,393	18,393	18,393	18,393	18,393
Adjusted R^2	0.681	0.775	0.778	0.722	0.791	0.784	0.792	0.792

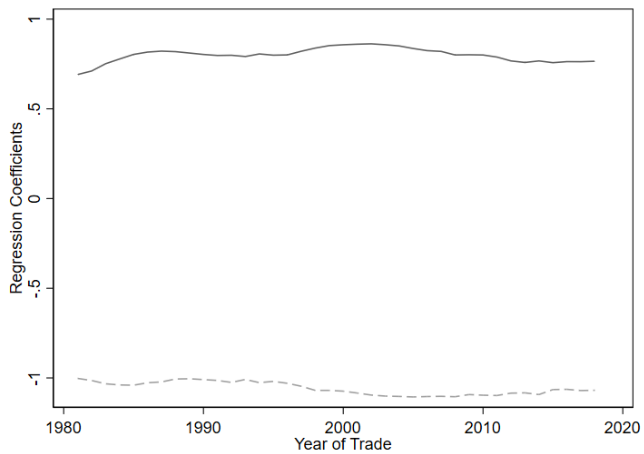
Note: Table shows results from regression B.1. We estimate the regression on non-zero trade observations (intensive margin) using OLS. The dependent variable is total exports from country i to country j. Controls include the logarithm of SCI, the logarithm of distance, a common border dummy, a common official language dummy, a dummy indicating whether the two countries had a common colonizer post-1945, a dummy indicating whether the pair of countries was in a colonial relationship post-1945 and percentiles of SCI. All specifications include exporter and importer country fixed effects. Standard errors are clustered by exporter and importer country. We have data on trade and social connectedness for 165 countries, which leads to 18,393 non-zero trade observations. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

B.3 Time-variation in Trade Elasticities

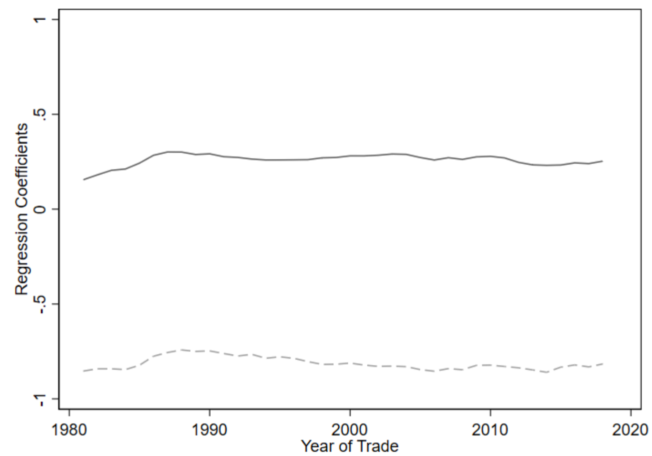
In this section, we examine how the elasticity of trade with respect to social connectedness and distance varies over time. For this purpose, we use *The Direction of Trade Statistics* from the IMF that reports aggregate bilateral trade data from 1948 to 2018. Because the earlier years contain a lot of missing trade entries and we want to keep the set of countries constant across time, we focus on the time period from 1981 to 2018. For each year, we regress aggregate bilateral trade on our distance measure and our social connectedness measure from August 2020. This allows us to estimate year-specific regression coefficients that are shown in Figure B.1. These findings highlight that the elasticity of trade to both distance and social connectedness has been highly constant over the past fourty years; the results also document that the underlying trade-facilitating relationships that we proxy for with the *Social Connectedness Index* are very stable over time.

Figure B.1: Time-variation in Elasticity of Trade to Social Connectedness

(A) Univariate Regressions



(B) Multivariate Regression



Note: Figures show year-specific regression coefficients from regressing trade on $\log(SCI)$ and $\log(Distance)$ as specified in Equation 2. Panel A shows the regression coefficients obtained in univariate regressions, and Panel B shows the regression coefficients obtained in multivariate regressions. The dark grey solid line shows the coefficient on social connectedness, while the light grey dashed line shows the coefficient on distance. Both regression specifications include exporter and importer country fixed effects.

B.4 Gravity Regressions – A Horse Race of Predictors

In Table 2 of the main paper, we regressed aggregate bilateral trade flows on the logarithm of social connectedness and other gravity variables. However, it might be instructive to look at how trade interacts with each of these variables individually, exploring the relative economic and statistical significance of each variable separately.

In this section, we conduct this analysis using both PPML regressions as well as OLS regressions that study the intensive margin of trade. We report the results of this "horse race of predictors" in Table B.2. Columns 1 to 6 are estimated using PPML, while columns 7 to 12 are estimated using OLS. Consistent with our other results, we find that distance and social connectedness are the most successful in explaining variation in bilateral trade. In the PPML regression, distance and social connectedness are the only two variables that individually explain more than 90% of bilateral trade after controlling for exporter and importer country fixed effects. A similar results emerges from the OLS regression: including distance and social connectedness raises the R^2 significantly compared to all other gravity variables.

Table B.2: Gravity Regressions - Aggregate Trade in 2017 - Horse Race

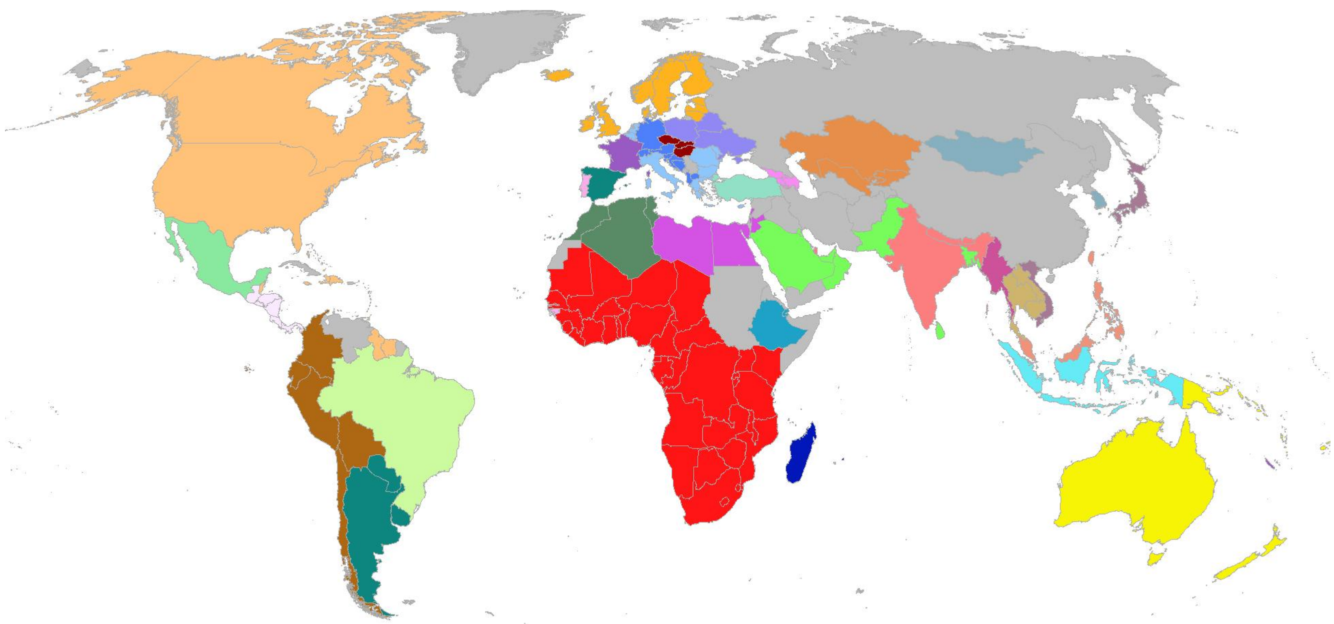
	PPML						OLS					
	Dependent variable: Aggregate Bilateral Trade						Dependent variable: log(Aggregate Bilateral Trade)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
log(Distance)	-0.992***						-1.711***					
	(0.0595)						(0.0650)					
log(SCI)		0.646***						0.773***				
		(0.0390)						(0.0272)				
Common Border			1.905***						4.317***			
			(0.208)						(0.244)			
Common Official Language				0.908***						1.800***		
				(0.145)						(0.167)		
Common Colonizer					1.509***						1.642***	
					(0.168)						(0.209)	
Colonial Relationship						0.353						1.287***
						(0.303)						(0.349)
Orig. and Dest. Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.935	0.921	0.891	0.848	0.843	0.837	0.778	0.775	0.705	0.701	0.691	0.682
N	27,060	27,060	27,060	27,060	27,060	27,060	18,393	18,393	18,393	18,393	18,393	18,393

Note: Table shows results from regression 2 (PPML) and regression B.1 (OLS). We estimate the regression using PPML in columns 1–6 and using OLS in columns 7–12. The dependent variable is total exports from country i to country j for the PPML regressions, and the logarithm thereof for the OLS regressions. Controls include the logarithm of SCI, the logarithm of distance, a common border dummy, a common official language dummy, a dummy indicating whether the two countries had a common colonizer post-1945, and a dummy indicating whether the pair of countries was in a colonial relationship post-1945. All specifications include exporter and importer country fixed effects. Standard errors are clustered by exporter and importer country. We have data on social connectedness for 165 countries, which leads to 27,060 (= 165 x 164) observations. The OLS regressions use only non-zero trade observations (intensive margin of trade). Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

B.5 Groups of Socially Connected Countries

One advantage of our measure of social connectedness is that it covers the vast majority of countries, allowing us to understand the structure of global social connectedness beyond just bilateral connections. In particular, we describe above that countries that share certain characteristics are more socially connected to each other. Such shared characteristics often lead us to think about groups of countries, such as "Spanish-speaking South America" or "Arab North Africa," where countries in the group are all similar to one another on some salient dimension. We next formalize the idea of groups of countries with strong connections amongst each other. We then use this grouping to show that trade patterns are influenced not only by direct social connections, but also by the social clusters that different countries are part of.

Figure B.2: Groups of Socially Connected Countries: 30 Clusters



Note: Figure shows countries grouped together when we use hierarchical agglomerative linkage clustering to create 30 distinct groups of socially connected countries.

There are a number of possible algorithms to construct clusters of countries that feature a high average within-cluster pairwise social connectedness. Here, we use hierarchical agglomerative linkage clustering to group countries into 30 clusters.[4] Figure B.2 shows the 30 different clusters and Table B.3 lists the countries in each cluster. The average number of countries per cluster is 6. There are four clusters that only contain a single country — Brazil, Mexico, Burma, and Turkey. By far the largest cluster with 36 countries contains all of Southern and Western Africa. All other clusters have substantially fewer countries, with the second and third largest clusters containing 16 and 10 countries, respectively.

[4]The agglomerative clustering algorithm starts by considering each of the N countries as a separate group of size one. In the first step, the two "closest" countries are merged into one larger group, producing $N-1$ total groups. In each subsequent step, the closest two groups are again merged. This process continues until all the countries are merged into a given number of clusters. We define the "distance" between two countries as the inverse of $SCI_{i,j}$: the lower the probability of a given Facebook user in country i knowing a given Facebook user in country j, the "further apart" socially the two countries are. We calculate the closeness between clusters with more than one country as the average distance between the countries in the cluster.

Table B.3: 30 Clusters of Socially Connected Countries

Cluster	Countries
1	Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Congo, Cote d'Ivoire, Democratic Republic of the Congo, Equatorial Guinea, Gabon, Gambia, Ghana, Guinea, Kenya, Lesotho, Liberia, Malawi, Mali, Mauritania, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Swaziland, Togo, Uganda, United Republic of Tanzania, Zambia, Zimbabwe
2	Antigua and Barbuda, Bahamas, Barbados, Belize, Canada, Cayman Islands, Dominican Republic, Grenada, Guyana, Haiti, Jamaica, Saint Lucia, Saint Vincent and the Grenadines, Suriname, Trinidad and Tobago, United States
3	Denmark, Estonia, Finland, Iceland, Ireland, Latvia, Lithuania, Norway, Sweden, United Kingdom
4	Albania, Austria, Bosnia and Herzegovina, Croatia, Germany, Malta, Slovenia, Switzerland, Republic of North Macedonia
5	Bahrain, Bangladesh, Kuwait, Maldives, Oman, Pakistan, Saudi Arabia, Sri Lanka, United Arab Emirates
6	Australia, Fiji, Kiribati, New Zealand, Papua New Guinea, Samoa, Solomon Islands, Tonga, Vanuatu
7	Belgium, Bulgaria, Cyprus, Greece, Italy, Netherlands, Republic of Moldova, Romania
8	Brunei Darussalam, Hong Kong, Macau, Malaysia, Philippines, Singapore, Taiwan
9	Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, Panama
10	Bolivia, Chile, Colombia, Ecuador, Peru
11	Cape Verde, Guinea-Bissau, Luxembourg, Portugal, Sao Tome and Principe
12	Egypt, Jordan, Lebanon, Libyan Arab Jamahiriya, Palestine
13	Argentina, Paraguay, Spain, Uruguay
14	Bhutan, India, Nepal, Qatar
15	Comoros, Madagascar, Mauritius, Seychelles
16	Armenia, Azerbaijan, Georgia
17	Belarus, Poland, Ukraine
18	Czech Republic, Hungary, Slovakia
19	Algeria, Morocco, Tunisia
20	France, French Polynesia, New Caledonia
21	Kazakhstan, Kyrgyzstan, Uzbekistan
22	Cambodia, Lao People's Democratic Republic, Thailand
23	Djibouti, Ethiopia
24	Indonesia, Timor-Leste
25	Japan, Viet Nam
26	Republic of Korea, Mongolia
27	Brazil
28	Mexico
29	Burma
30	Turkey

Note: The table reports 30 groups generated by hierarchical agglomerative linkage clustering.

Different characteristics shape the different clusters. For instance, countries in Central America form one cluster, consistent with the importance of geography. Spain, however, forms a cluster with Argentina, Uruguay, and Paraguay, highlighting that not all clusters are geographically contiguous and pointing at shared language as another important factor. The cluster comprised of Mongolia and South Korea reflects both a long common history and common ethnic ancestry, as well as recent migration of Mongolians to South Korea. While standard characteristics can explain some of the variation in clustering, it is important to note that these clusters are constructed from our social connectedness measure that has substantial variation beyond standard gravity characteristics.

Groups of Socially Connected Countries and Trade. We next explore the effect on trade of two countries sharing connections to a similar set of other countries, over and above the direct effect of the bilateral connections between those two countries. There are several mechanisms through which being in the same social cluster of countries could increase trade. Conceptually, being in the same social cluster can increase trade by alleviating search frictions. If country A and B are both connected to country C, traders in country A can use existing links to country C in order to establish connections with potential trading partners in country B. We build two measures of whether countries share social connections with a similar set of other countries. Our first measure is simply a dummy variable for whether countries are in the same one of the 30 clusters, though our results are robust to variations in the cluster size. Our second measure captures whether countries are placed into the same cluster at an early, middle, or late stage of the agglomerative clustering process.[5] The advantage of this measure is that it does not require us to take a stand on the number of clusters we put countries into.

We present the results from this analysis in Table B.4. For comparison, in column 1 we present our baseline specification for aggregate trade, corresponding to column 7 of Table 1. In column 2, we control for whether countries are in the same cluster when splitting the world into 30 groups. Conditional on the bilateral social connectedness and other gravity variables, being in the same cluster increases trade substantially. As an example, Spain is approximately equally well-connected to the United Kingdom and to Argentina, but it only shares a cluster with Argentina. Our estimates suggest that, all else equal, Spain would thus trade 33% more with Argentina than with the United Kingdom.

In column 3, we interact the number of countries (in logs) in the cluster with the same-cluster dummy variable. We see that the effect on trade of being in the same cluster increases when the cluster includes a larger number of other countries. In column 4, we add the dummy variables for when countries join the same cluster. We find that, controlling for the direct effect of bilateral social connectedness as well as the other gravity variables, countries which join the same cluster early rather than late have 21% higher bilateral trade. To rule out that these effects capture a non-linear relationship of bilateral social connectedness and distance on trade, columns 5-7 introduce controls for percentiles of both social connectedness and geographic distance. Our results remain qualitatively unchanged compared to the estimates in columns 2-4. Overall, we conclude that beyond the effect of direct social connections, being in the same social cluster substantially increases bilateral trade between countries.

[5] Agglomerative clustering is a sequential procedure where at each stage countries are merged into clusters. Merging tends to occur earlier in the process if countries are closer socially. Due to the nature of the hierarchical clustering algorithm, most countries do not join the same cluster until the last stage. We use cutoffs of 95% and 90% to put country pairs into 3 groups for when they join the same cluster. These cutoffs correspond to the 18th and 41st clustering steps.

Table B.4: Gravity Regressions - The Role of Social Clusters

	Dependent variable: Aggregate Exports						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(SCI)	0.280***	0.262***	0.280***	0.267***			
	(0.026)	(0.025)	(0.023)	(0.025)			
Same Cluster (30 Gr.)		0.286***	-0.544*		0.324***	0.132	
		(0.079)	(0.298)		(0.071)	(0.239)	
Join Same Cluster - Middle				0.144			0.160**
				(0.100)			(0.069)
Join Same Cluster - Early				0.214*			0.433***
				(0.116)			(0.114)
Same Cluster (30 Gr.) $\times$ log(Cluster Size)			0.389***			0.091	
			(0.146)			(0.106)	
Orig. and Dest. Country FE	Y	Y	Y	Y	Y	Y	Y
Other Gravity Controls	Y	Y	Y	Y	Y	Y	Y
SCI Group FE					Y	Y	Y
Distance Group FE					Y	Y	Y
R^2	0.943	0.944	0.944	0.943	0.951	0.951	0.951
N	27,060	27,060	27,060	27,060	27,060	27,060	27,060

Note: Table shows results from regression 2. The dependent variable is total exports from country *i* to country *j*. "Same Cluster (30 Gr.)" is a dummy variable indicating that the two countries are in the same cluster when we create 30 clusters using the hierarchical clustering algorithm described in Section 1. "Join Same Cluster" indicates whether countries are placed into the same cluster at an early, middle, or late stage of the agglomerative process. Other gravity controls include the logarithm of distance, a common border dummy, a common official language dummy, a dummy indicating whether the two countries had a common colonizer post-1945, and a dummy indicating whether the pair of countries was in a colonial relationship post-1945. We also separately control for distance and SCI groups (dividing distance and SCI into percentiles) in columns 5 to 7. All specifications include fixed effects for the importer and exporter country. Standard errors are clustered by exporter and importer country. We have data on trade and social connectedness for 165 countries and 27,060 (=165 x 164) observations. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

C Trade and Subnational Social Connectedness in Europe

In this section, we explain the construction of the data used in Section 3 when analyzing trade and subnational social connectedness across European regions.

C.1 Construction of Data for Input-Output-Weighted Connectedness

Our analyses in Section 3.1 use information on employment at the industry-NUTS2 region level, mapped to input-output data at the industry-country level and trade data at the product-country level (as described in the text, we use product and industry interchangeably). The final analyses include 28 countries for which all three sets of data were available.[6] The industry employment data come from the Eurostat Structural Business Statistics series, which includes employment in NUTS2 regions for NACE Rev. 2 industry classifications at the division level.[7] In each region, we use the most recent year in which the data were available starting with 2017. 64% of the data come from 2017, 26% from 2016, 1.6% from 2015, 1.3% from 2014, and 3.22% from between 2013 and 2008. Observations prior to 2016 may be categorized using different NUTS2 regions, as these boundaries periodically change. In instances when we use an observation prior to 2016 in a region that changed, we use a crosswalk described in Section C.2, below.[8] For each industry and country, we calculate the share of employment in each region (e.g. the share of Greek construction industry workers that are in the Attica Region).

We then match these data to the World Input-Output data by country and industry of origin and destination. Our mapping from NACE Rev. 2 industry classifications to the World Input-Output classifications comes from correspondence tables provided by Eurostat. We then add product-level trade data from CEPII by mapping the Harmonized Commodity Description and Coding System (HS96) product classifications to the World Input-Output industry classifications. This mapping comes from correspondence tables provided by the World Bank, UN Statistics Division, and Eurostat. For the purpose of our analysis, our focus is on goods that are used as an intermediate input to another production process in the country of destination. Accordingly, we drop industries for which more than half of the exports are used for final consumption. Our final analysis includes the 20 industries listed in Table C.1.

C.2 Construction of Rail Freight Data

Our analyses in Section 3.2 use information on European region-to-region rail goods transportation from Eurostat. The data are based on individual reports from European Union members, European Free Trade Association members, and European Union candidates. The data are reported for 2005, 2010, and 2015, in accordance with Directive 80/1177/EC of the European Commission and subsequent regulatory updates. We use the 2015 data and prepare them for our analyses as described below. This process was informed by the "Reference Manual on Rail Transport Statistics" and our correspondence with the Eurostat data providers.

[6]These countries are Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Spain, Sweden, Slovenia, Slovakia and the United Kingdom.

[7]Notably, the SBS series does not cover agriculture, forestry, and fishing. For more information on the series see: https://ec.europa.eu/eurostat/web/structural-business-statistics. For more information on NACE Rev. 2 classifications see: https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/KS-RA-07-015.

[8]Here, the necessary assumption we make for regions that split is that employment by industry in each new region is proportional to 2015 populations.

Table C.1: Products Used in Input-Output-Weighted Regressions

Industry
Architectural and engineering activities; technical testing and analysis
Electricity, gas, steam and air conditioning supply
Manufacture of basic metals
Manufacture of chemicals and chemical products
Manufacture of coke and refined petroleum products
Manufacture of computer, electronic and optical products
Manufacture of electrical equipment
Manufacture of fabricated metal products, except machinery and equipment
Manufacture of machinery and equipment n.e.c.
Manufacture of motor vehicles, trailers and semi-trailers
Manufacture of other non-metallic mineral products
Manufacture of other transport equipment
Manufacture of paper and paper products
Manufacture of rubber and plastic products
Manufacture of wood/products of wood and cork, except furniture; manufacture of straw articles and plaiting materials
Mining and quarrying
Other professional, scientific and technical activities; veterinary activities
Other service activities
Printing and reproduction of recorded media
Publishing activities

Note: Table shows the 20 industries that are included in the input-output-weighted analyses in Section 3.1. Industry descriptions come from the NACE Rev. 2 European statistical classifications of economic activities.

We first restrict the data to observations that are at the NUTS2 region level, including country-level data for countries which consist of only a single NUTS2 region. We exclude all pairs that include a region with the unknown indicator "XX" or the extra-regio territory indicator "ZZ".[9] From here, we are faced with four challenges: 1) As confirmed by the authors' correspondence with Eurostat, when the data appear as "non-available" in a particular row, this could mean either that there was no rail traffic or that the relevant country did not provide the data.[10] 2) There are a number of hypothetical region pairs missing, even between countries that did report data elsewhere. 3) For some international region pairs, there are data reported from both countries on the same train flows, and the reported tons of goods transported does not match. 4) The 2015 data are reported by 2013 NUTS2 region, while our social connectedness and distance data are reported by 2016 NUTS2 region.

With respect to challenges 1 and 2, we use the fact that each country reports data to Eurostat in two intermediate data sets: one for domestic transport of goods and another for international transport of goods. To identify countries that submitted a particular set of data in a particular year, we group the data by the reporting country, year, and whether the region pair is international or domestic. We then generate a list of countries that had at least one non-missing entry in each year/domestic-international group. These lists are provided in Table C.2. When "non-available" values are reported by a country that *did not* report data elsewhere in the year/domestic-international group, we treat the observation as missing and exclude it. When "non-available" values are reported by a country that *did* report data

[9]Observations with these two codes make up 4.9% of tonnage transported in the data.

[10]In some instances, countries report the data to Eurostat, but flag them as confidential so that they are not included in the public release. We always treat these data as missing in our final analysis.

elsewhere in the group, we treat this value as a zero (no traffic). Additionally, for countries that reported data in a particular group, we fill any missing region pairs (i.e. pairs that are not in the data) in the group with zeros. Together, these assumptions handle challenges 1 and 2.

For each international region pair, there still remain two possible reports: one from each of the regions' home countries in the pair. In instances when only one country reports the data, we take the non-missing value from the reporting country. However, there are a number of instances when each country reports data for the same international region pair (challenge 3). In these instances, we take the average of the two reports.[11] Finally, to update the data to the 2016 NUTS2 regions (challenge 4) we build a crosswalk using the history of NUTS information provided by Eurostat.[12] In instances when a 2013 NUTS2 region split into multiple regions, we set the tons of goods transported in each of the 2016 NUTS2 observations equal to the corresponding 2013 NUTS2 region tons of goods transported, multiplied by the region's 2015 population share (i.e. we assume that tons of goods transported in each of these regions is proportional to the 2015 population).

Table C.2: Rail Freight Data Availability By Reporting Country

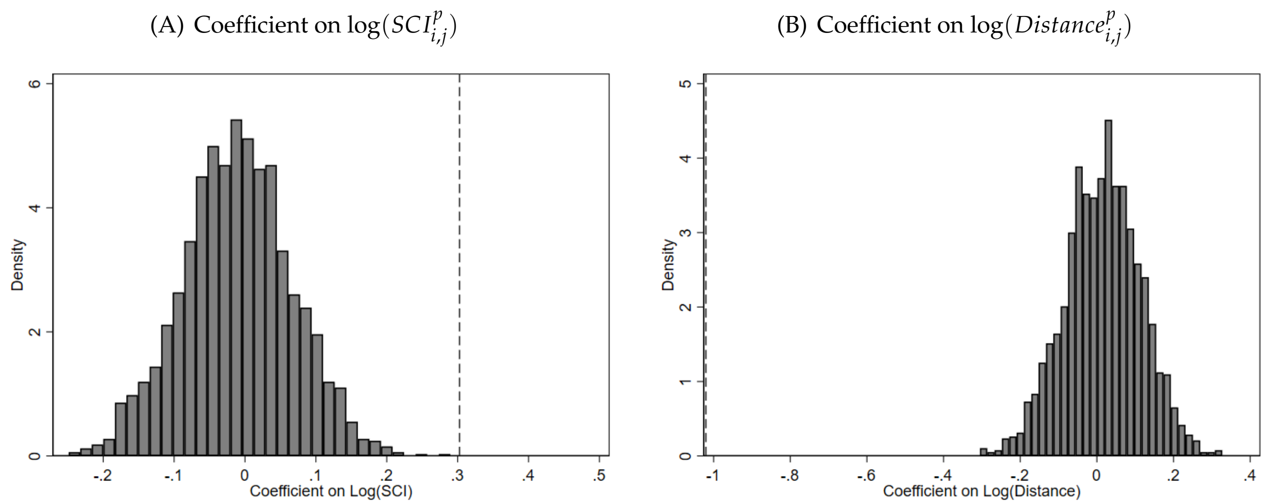
Reporting Country	Domestic Data	International Data	Reporting Country	Domestic Data	International Data
Albania	N	N	Lithuania	Y	Y
Austria	N	N	Luxembourg	Y	Y
Belgium	N	N	Malta	N	N
Bulgaria	Y	Y	Montenegro	N	N
Croatia	Y	Y	Netherlands	Y	N
Cyprus	N	N	Norway	Y	Y
Czech Republic	Y	Y	Poland	Y	Y
Denmark	Y	Y	Portugal	Y	N
Estonia	Y	Y	Romania	Y	N
Finland	Y	Y	Serbia	N	N
France	N	N	Slovakia	Y	Y
Germany	Y	Y	Slovenia	Y	Y
Greece	N	N	Spain	Y	Y
Hungary	N	N	Sweden	N	N
Iceland	N	N	Switzerland	N	N
Ireland	Y	Y	North Macedonia	N	N
Italy	Y	Y	Turkey	Y	N
Latvia	Y	Y	United Kingdom	N	N
Liechtenstein	N	N			

Note: Table shows the rail goods transportation data availability by reporting country and by type of trade (domestic or international). Y (N) indicates the data are (not) available. The table only shows availability at the reporter level, not whether any regions from this country are included in the final analysis. For example, although Austria did not report international data in 2015, pairs that include an Austrian region and a region in a country that did report international data in 2015 are nevertheless included.

[11] In few instances, a "third-party" country will report transport between regions in two other countries. We exclude these observations from our analysis.

[12] Available at: https://ec.europa.eu/eurostat/web/nuts/history

Figure C.1: Randomization Inference



Note: Figures show the distribution of regression coefficients for randomly selected values of social connectedness and distance. Panel A shows the coefficients for social connectedness, and Panel B the coefficients for distance. The regression specification is equal to column 4 in Table 3; namely it is a regression of industry-level trade between countries on industry-specific measures of social connectedness and distance. The coefficients obtained in the original regression are shown as the dashed lines. We contrast the actual estimates with regression coefficients that are obtained when choosing "random" values for social connectedness and distance. To be more precise, for each country i × country j × product p triplet, we assign a value of $\log(SCI^p_{i,j})$ and $\log(Distance^p_{i,j})$ from a randomly chosen product in the same country pair. We then estimate a regression based on these "random" values and repeat this exercise 2,000 times. The distribution of estimated coefficients is then plotted in a histogram.

C.3 Randomization Inference

An alternative way of exploring the statistical significance of the estimates in column 4 of Table 3 is the following. For each country i × country j × product p triplet, we assign a value of $\log(SCI^p_{i,j})$ and $\log(Distance^p_{i,j})$ from a randomly chosen product in the same country pair, and then re-run the regression. We repeat this exercise 2,000 times. The histograms in Figure C.1 show the distribution of the coefficients on the re-shuffled values of input-output-weighted social connectedness and distance; the dashed lines shows the estimated effect corresponding to column 4 of Table 3. The randomized coefficients are centered around zero: conditional on country pair fixed effects, there is no additional explanatory power for trade in a given product coming from variation in input-output-weighted social connectedness of a random product. Said differently, what matters is not the social connectedness of regions involved in trade generally; instead, what matters for the trade in a specific product is the social connectedness across regions that produce and use that specific good.