Cultural Proximity and Inter-firm Trade[*]

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First draft: April, 2022
This draft: May, 2024

Abstract

Emerging economies sometimes have low-quality institutions, generating micro-level trade frictions. In these settings, firms may rely on informal institutions, such as cultural proximity, to overcome such frictions. Using new microdata on firm-to-firm trade from India with information on prices, transactions, and caste and religious connections, we find that higher cultural proximity reduces prices and fosters trade at intensive and extensive margins. When exploring potential mechanisms, we find evidence supporting the role of cultural proximity in alleviating contracting frictions. We formalize these findings by building an inter-firm trade model with cultural proximity between firm owners. Our counterfactual exercises indicate that an economy composed of culturally closer firms features lower costs, lower prices, higher sales, and higher welfare than an economy with culturally distant firms.

Keywords: cultural proximity, inter-firm trade, domestic trade, contracting frictions, contract enforcement, social inclusion

JEL Codes: D51, F19, O17

1 Introduction

Non-economic forces, such as *culture*— religion, language, values, etc.— may drive economic outcomes. The role of culture on agent behavior has been well documented in entrepreneurship, loan access, labor markets, marriage, development, and cross-country international trade (Fisman et al., 2017; Goraya, 2023; Munshi and Rosenzweig, 2016; Rauch, 1996; Rauch and Trindade, 2002; Startz, 2016; Artiles, 2023). Nevertheless, the mechanisms by which cultural proximity shapes trade between firms remain less understood. Understanding how and why cultural proximity affects inter-firm trade potentially allows policy-makers to better leverage social inclusion programs and foster economic development.

We first provide empirical evidence on the role of cultural proximity in inter-firm trade. To do this, we leverage a unique dataset of transactions between firms from a large Indian state, along with data on firm owners' names and their cultural proximity derived from India's caste and religious system. We report three new stylized facts. First, culturally closer firms report higher sales between them: the higher the cultural proximity, the higher the trade on the intensive margin. Second, culturally closer firms are more likely to ever trade with each other. That is, the higher the cultural proximity, the higher the trade on the extensive margin as well. Third, firms that are culturally further apart report higher unit prices in their transactions. All these results are robust to an array of high-dimensional fixed effects, including seller and buyer fixed effects, origin-by-destination fixed effects (and for specifications with product and time, seller-by-product, and product-by-month fixed effects).

We then turn to explore various mechanisms, and find evidence most in line with the importance of contract enforcement. First, we show that the effect we find of cultural proximity on trade is driven by differentiated products, which often rely on either formal or informal contract enforcement (Nunn, 2007; Rauch, 1999).[1] Second, cultural proximity matters the most when institutional quality, proxied by the court quality in the districts where the trade partners belong, is particularly low. We argue that, in a setting with low institutional quality and poor contract enforcement, firms that trade differentiated goods rely on informal institutions (i.e. cultural proximity) as a substitute for the imperfect formal ones. We understand these findings as evidence that cultural proximity relates to contract enforcement and trust (Munshi, 2019, 2014).[2]

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[1]Differentiated goods do not trade in exchanges and are not homogeneous, but are branded and specific to certain producing firms. In a country with market imperfections as India, firms can easily renege on their commitments. Suppliers and buyers in differentiated goods markets are not easily replaceable. In such cases, trade will increase when firms trust and know each other, that is, when they are culturally close.

[2]Munshi (2019) uses survey data to show that Indians trust people from their caste.

We further find that the more varieties a firm sells or buys, the more the trade intensity is affected by cultural proximity. We posit that the larger the number of different varieties a firm sells or buys, the more firms it has to negotiate with, which increases the contracting frictions it faces. Then, to minimize the contracting frictions they face, firms will rely more on trading with culturally closer firms they trust.

We do not find sufficient evidence that hierarchies (and preference-based discrimination) across social groups matter, or that linguistic distance and the specialization in certain goods matters for our cultural proximity results. To analyze whether our results are caused by vertical social hierarchies and discrimination across cultural groups, we study asymmetric effects in those transactions where one firm is placed higher than the other based on the caste-based hierarchy, allowing us to test for preference-based discrimination across the social hierarchy. In other tests, we find our results are less likely to be driven by firms sharing the same language or sharing specialization in the production of certain goods.

We next conduct a counterfactual analysis to study the importance of cultural proximity for inter-firm trade. We build a quantitative trade model with cultural proximity between firms. Firms optimally decide whom to trade with subject to matching fixed costs, and how much to trade with subject to iceberg trade costs. In line with our empirical findings, we allow these costs to depend on how culturally close firms are.[3]

The model derives equations that precisely match their empirical counterparts in the previous section. We use these equations to estimate the key parameters of the model: the semi-elasticity of the trade cost to cultural proximity and the semi-elasticity of matching cost to cultural proximity. Our model allows us to estimate both of these parameters externally. In line with our stylized facts, we find a negative semi-elasticity of both the intensive and extensive margin of trade to cultural proximity. This implies the closer two firms are in cultural terms, the lower the trade and matching costs are. Therefore, the higher the cultural proximity for a pair of firms, the higher the trade is on both the intensive and extensive margins, and the lower the prices charged.

We then use the model and estimated parameters to quantify the implications for welfare and other aggregate outcomes of implementing different policies. First, we evaluate the effects of social mixing/inclusion (i.e. firms become culturally the closest possible) and social isolation

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[3]On the extensive margin, cultural proximity between firms can reduce matching costs since culture encodes useful information for sellers to decide who to sell to (Balmaceda and Escobar, 2017; Ali and Miller, 2016). On the intensive margin, sellers charge a premium to buyers arising from contracting frictions. Given the risk of reneging on the contract or delaying payment, sellers determine the charged premium to buyers, and so affect the intensive margin of trade (Boehm and Oberfield, 2020)

policies (i.e. firms become culturally the furthest possible). Second, we study the effects of a policy that reduces contracting frictions, such that firms rely less on cultural proximity when trading (i.e. trade and matching costs become less sensitive to cultural proximity). We find that welfare increases by 1.76 percent under a diversity-friendly social inclusion policy. In contrast, welfare falls by 1.45 percent when we evaluate the effects of social isolation or exclusion. Finally, we show that policies that reduce contracting frictions raise welfare by 0.87 percent by reducing the reliance of trade on cultural links.

Figure 1: Probability-weighted sales decomposition of largest cultural groups

(a) Largest Hindu group: Nair (b) Largest non-Hindu group: Muslims
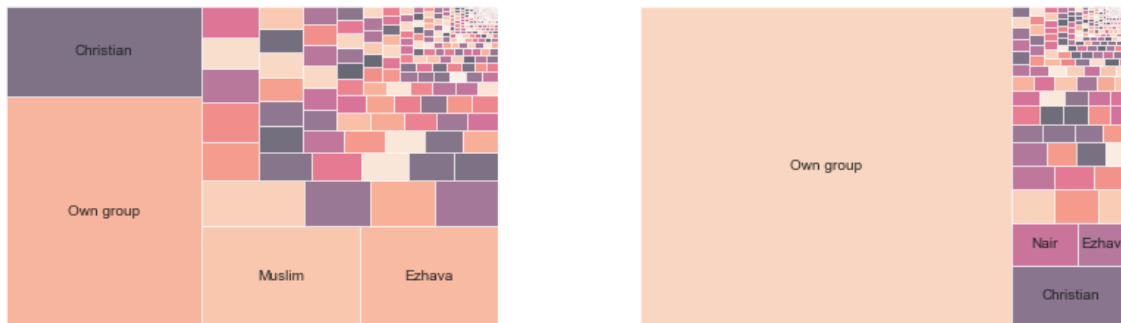
Notes: The figure shows the decomposition across buyers for the largest Hindu and non-Hindu cultural groups measured by probability-weighted sales. For instance, the Nair and Muslims accounted for 5.39 and 19.68 percent of total probability-weighted sales, respectively.

The analysis of cultural proximity is especially relevant for developing countries, where agents face several contracting frictions and, consequently, rely more on non-economic forces. In particular, India has a society that follows the parameters of a caste system, which also intertwines with the different religious groups.[4] In this case, cultural proximity naturally arises as a product of the inherent hierarchical structure of the caste system and the different religions. Related to this, Figure 1 shows an example of how trade between cultural groups occurs, in a selected subset of our data. We can see that there are cultural groups that are bound to trade more or less with other cultural groups. We thus ask whether cultural proximity, measured as the cultural group-based distance between firms, can determine trade.

We contribute to two strands of the literature. First, we speak to the role of cultural proximity on trade (Bandyopadhyay et al., 2008; Guiso et al., 2009; Macchiavello and Morjaria,

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[4]In this paper, we consider the caste system and religious groups as a proxy for cultural groups. There is a large historical legacy for the caste system to be considered a discrimination device, which we consider. Even though there is an active agenda of the government to implement policies that hinder caste-based discrimination, it is still used by Indians as a way to determine how similar individuals are between them.

2015; Rauch, 1996; Rauch and Casella, 2003; Rauch and Trindade, 2002; Richman, 2006; Schoar et al., 2008; Startz, 2016; Zhou, 1996; Boken et al., 2022). Cultural differences in international trade or across administrative regions also interplay with non-cultural barriers. In contrast, we use transaction-level firm-to-firm data to explore the effect of culture on trade that does not rely on cross-border variation. This allows us to isolate the mechanisms at a granular level, and to provide a framework that quantifies the role of cultural proximity for inter-firm trade.[5] We also connect to the importance of cultural or social proximity on other economic outcomes, like entrepreneurship (Goraya, 2023), finance (Fisman et al., 2017), the composition of the board of directors (Faia et al., 2021), and labor markets (Munshi and Rosenzweig, 2016). We complement this work by examining how culture affects trade frictions. Understanding the source of these frictions or even leveraging them is key to adequately determining the consequences of economic policy.

Second, we contribute to the literature on social cohesion (Alan et al., 2021; Alesina and Giuliano, 2015; Alesina et al., 2021; Alesina and Reich, 2015; Bazzi et al., 2019; Depetris-Chauvin et al., 2020; Gradstein and Justman, 2019; Ritzen et al., 2000) and contract enforcement policies.[6] We contribute by implementing a policy counterfactual analysis that quantifies the aggregate effects of education and court quality policies through cultural proximity.

The rest of the paper is structured as follows. In Section 2 we provide a brief review of the caste system in India, describe our new datasets, and explain how we construct firm-level trade and cultural proximity variables. In Section 3, we report our stylized facts, study the mechanisms driving the effect of cultural proximity on trade, and robustness checks. In Section 4, we briefly describe the model, how we estimate the model, and perform a counterfactual analysis. Section 5 concludes.

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[5]In ongoing work, Boken et al. (2022) also shows the role of cultural proximity for inter-firm trade. We mainly distinguish ourselves by leveraging data on prices, which allows us to estimate how cultural proximity influences inter-firm trade through the alleviation of contracting frictions. Additionally, we explore a rich set of mechanisms, as our data contains information to test how cultural proximity matters for inter-firm trade through discrimination (caste hierarchies), order cancellations, firm survival over age, and how cultural proximity matters for firm-level complexity. Leveraging other data, we implement a Heckman selection bias correction model to estimate trade elasticities following Helpman et al. (2008).

[6]Contracting frictions can be either formal or informal. We show that informal channels, such as cultural proximity, matter in the aggregate when implementing policies.

2 Background, data and construction of variables

2.1 Caste and Religion in India

India has a society that is heavily influenced by the parameters of a caste system: a hierarchical system that has prevailed in the country since around 1,500 BC and that still rules its economy. According to this classification, people are classified across four possible groups called *Varnas*. From the most to the least privileged in hierarchical order, the four Varnas are *Brahmins*, *Kshatriyas*, *Vaishyas*, and *Shudras*. The Brahmins have historically enjoyed the most privileges, and are traditionally comprised of priests and teachers. The Kshatriyas are next in the hierarchy, usually associated with a lineage of warriors. The Vaishyas are third and are related to businessmen such as farmers, traders, among others. Finally, the Shudras are the most discriminated against and are the caste formed to be the labor class. Below these groups in the socio-economic hierarchy, were marginalized groups called Dalits.

At the same time, Varnas are comprised of sub-groups called *Jatis*, determined by factors such as occupation, geography, tribes, or language. In that sense, using Jatis as castes is appropriate for studying economic networks (Munshi, 2019), and from here on, we use the notion of Jatis when referring to castes.

We also consider religious groups to define other cultural groups. The caste system is inherently based on Hindu religion, the predominant religion in India. While other religions in India did not historically follow the caste system, they do relate to it today: the other non-Hindu religions work as cultural groups of their own. We leverage information on firm owners belonging to both caste and non-Hindu religious groups to construct our measure of cultural proximity.

2.2 Data

Firm-to-firm trade. We obtain a new firm-to-firm trade dataset for a large Indian state provided by the state's corresponding tax authority.[7] We use daily transaction-level data from January 2019 to December 2019, as long as at least one node of the transaction (either origin or destination) was in the state. This data exists due to the creation of the E-Way bill system in India in April 2018, where firms register the movements of goods online for tax purposes. This is a major advantage over traditional datasets collected for tax purposes

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[7]While we use the term 'firm' in most parts of the paper, these data are actually at the more granular establishment level.

in developing countries since the E-Way bill system was created to significantly increase tax compliance.[8]

The state has a diversified production structure, roughly 50 percent urbanization rates, and high levels of population density. To compare its size in terms of standard firm-to-firm transaction datasets, the population of this Indian state is roughly three times the population of Belgium, seven times the population of Costa Rica, and double the population of Chile. In addition, we can uniquely measure product-specific prices for each transaction, along with the usual measures of the total value traded.

Each transaction reports a unique tax code identifier for both the seller and buyer. We use these identifiers to merge this data with other firm-level datasets. We also have information on all the items contained within the transaction, the value of the transaction, the 6-digit HS code of the traded items, the quantity of each item, and the units the quantity is measured in. Since the data report both value and quantity of traded items, we construct unit values for each transaction. Each transaction also reports the pincode (zip code) location of both selling and buying firms. By law, any person dealing with the supply of goods and services whose transaction value exceeds 50,000 Rs (600 USD) must generate E-way bills. Transactions that have values lower than 600 USD can also be registered, but it is not mandatory. There are three types of recorded transactions: (i) within-state trade, (ii) across-state trade, and (iii) international trade. For this paper, we ignore international trade.

Firm owner names. Information about the name of firm owners comes from two different sources. The first is also provided by the tax authority of the Indian state, which is a set of firm-level characteristics for firms registered within our large state. Among these variables, we are provided with the name of the owner, directors and/or representatives of the firm.

To obtain firm-level characteristics of firms not registered in this state, we scrape the website *IndiaMART*,[9] the largest e-commerce platform for business-to-business (B2B) transactions in India. The website is comprised of firms of all sizes. By 2019, the website registered around 5-6 million sellers scattered all around India. Most importantly, this platform provides the

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[8]Tax evasion rates are thought to have fallen with the E-Way bill system, given how it is implemented. A selling establishment must online register the transaction, and print out a receipt that the driver of the transportation (usually a truck) must carry with them while transporting the product. If the driver is stopped or checked at any of the numerous checkpoints, and fails to produce a receipt, the goods are confiscated. Furthermore, the earlier VAT regime was only for large firms, and the new GST system was aimed at including smaller firms too. For more details about the new E-Way bill system, see https://docs.ewaybillgst.gov.in/

[9]https://www.indiamart.com/

name of the owner of the firm and the unique tax code identifier. Thus, we use the platform to obtain these variables for out-of-state firms.

Matching owner names to cultural groups. We follow Bhagavatula et al. (2018) to match owner names to their Jatis (if the owners are of Hindu religion) or to their religion (in case the owners are not Hindu). Their procedure consists of using scraped data from Indian matrimonial websites that contain information on names, castes, and religions. They train a sorting algorithm that uses names as inputs and gives a probability distribution across cultural groups per name as outputs. We match these probability distributions to each owner's name in our dataset. Notice that our notion of cultural group-belonging is probabilistic and not deterministic. This probabilistic approach is more relevant to our setup since, when firm owners trade with each other, they do not know each other's cultural group *ex ante*. Our sample finally consists of 452 cultural groups.

Figure 2: Probability-weighted sales and purchases across cultural groups
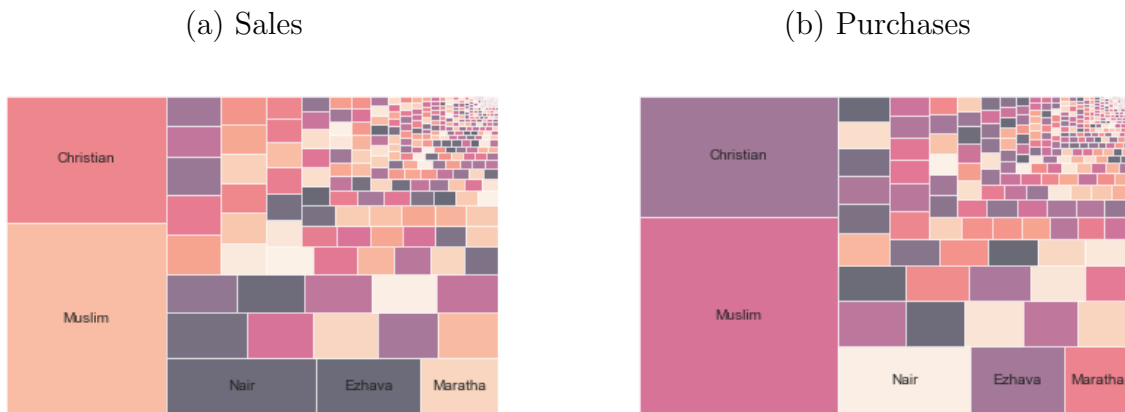
(a) Sales   (b) Purchases

Notes: Figure shows the decomposition of the probability-weighted sales and purchases across the 452 cultural groups in our dataset. The size of the rectangles reflects the share of sales and purchases.

Merged dataset. For the analytical part, we merge the three previous datasets. We end up with a sample that contains information from 22,295 unique firms, of which there are 10,559 sellers and 16,980 buyers. In total, the sample comprises approximately 560 thousand transactions or 97 billion rupees (around 1.4 billion US dollars). We drop any registered transaction in which the seller and the buyer are the same parent firm. Each firm is linked to a unique pincode. Finally, we assign a sector to each firm based on the ISIC codes of the goods sold. To provide a summary of the heterogeneity of cultural groups present in the firm-to-firm trade data, we show the distribution of probability-weighted sales and purchases across cultural groups in Figure 2.

2.3 Construction of variables

Inter-firm trade variables. The firm-to-firm dataset provides information at the transaction level between any two registered firms. More specifically, we have information on (i) transaction-level unique identifiers, (ii) seller and buyer unique identifiers, (iii) the 6-digit HS description of the traded goods in each transaction, (iv) the total value of the transaction in rupees per type of good involved in each transaction and (v) the number of units sold of each good in each transaction.

For every seller/buyer pair, we construct total sales, the total number of transactions, and unit values. For the total sales, we add up all the sales between each given pair of firms in our sample. We do the same with the total number of transactions. To obtain prices, we calculate the unit values. We first calculate the total amount sold and the total units sold of each good at the 6-digit HS level between each given pair of firms in our sample. Then, we divide the total amount sold by the number of units sold for each good.

Cultural proximity. Consider the set $\mathcal{X}$ of cultural groups, where $|\mathcal{X}| = X = 452$ in our final dataset. Since not all names are deterministically matched to a cultural group, each firm in our dataset has a discrete probability distribution over the set X of cultural groups. In particular, every firm ν has a probability distribution $\boldsymbol{\rho_\nu} = [\rho_\nu(1), \ldots, \rho_\nu(X)]$, such that $\sum_{x=1}^{X} \rho_\nu(x) = 1$. In this part, we distinguish between the probability distribution over cultural groups of the seller and the probability distribution over cultural groups of the buyer. Define $\rho_\nu(x)$ as the probability of seller ν of belonging to cultural group x. Similarly, define $\rho_\omega(x)$ as the probability of buyer ω of belonging to cultural group x. Based on these two distributions, we construct the following measure of cultural proximity: the Bhattacharyya coefficient (Bhattacharyya, 1943).

The Bhattacharyya coefficient between seller ν and buyer ω measures the level of overlap between two different probability distributions.[10] We define it as

$$BC(\nu, \omega) = \sum_{x=1}^{X} \sqrt{\rho_\nu(x) \rho_\omega(x)}.$$

Because $0 \leq \rho_\nu(x) \leq 1$ and $0 \leq \rho_\omega(x) \leq 1$, we have that $0 \leq BC(\nu, \omega) \leq 1$. On the one hand, $BC(\nu, \omega) = 0$ means the seller has a completely different probability distribution from the buyer's. In our context, this means the seller and the buyer have almost no chance of

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[10]Notice the Bhattacharyya coefficient is not the Bhattacharyya distance, which is defined as $BD(s, b) = -\log(BC(s, b))$. We prefer the Bhattacharyya coefficient because it is easier to interpret.

belonging to the same cultural group or that their cultural proximity is the farthest. On the other hand, $BC(\nu, \omega) = 1$ means the seller has the same probability distribution as the buyer. This implies that the seller has the same probability of belonging to a group of certain cultural groups as the buyer or that their cultural proximity is the closest possible.[11] In robustness checks, we use the Kullback and Leibler (1951) divergence measure (Appendix B.2). All our results are qualitatively similar, and statistically significant when doing so.

3   Stylized facts

Fact 1: Cultural proximity fosters trade.   We first discuss results related to the intensive margin of the firm-to-firm trade. Figure 3 shows the residualized scatterplots between the Bhattacharyya coefficient and two intensive margin measures: total sales between two firms and total transactions between two firms. The scatterplots show a higher Bhattacharyya coefficient (buyer and seller are probabilistically more alike in their cultural group) is related to a higher amount of sales and transactions.

Figure 3: Effect of cultural proximity on trade, intensive margin

(a) Sales
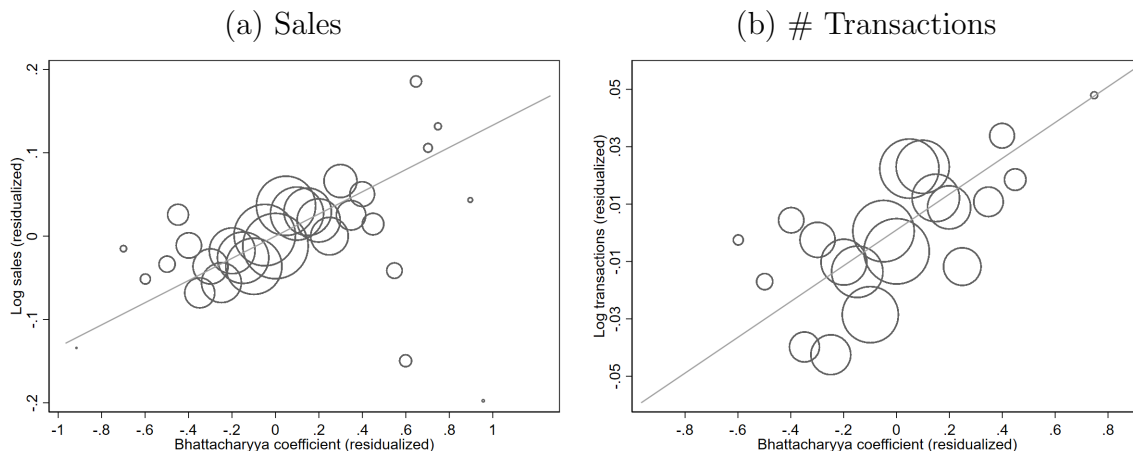
(b) # Transactions

Notes: Results are residualized of seller fixed effects, buyer fixed effects, and log distance. Equally distanced bins formed over the horizontal axis. The size of the bubbles represents the number of transactions in each bin. The higher the Bhattacharyya coefficient, the culturally closer the two firms are.

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[11]For our purposes, it is important that the cultural proximity measure we use is symmetric. To see why, consider an example where, in our dataset, we have a transaction between a seller ν and a buyer ω, from which we obtain $BC(\nu, \omega)$. Further, assume that in our dataset, we record a second transaction in which the roles of the firms revert (i.e. the buyer becomes the seller and vice versa), so we calculate $BC(\omega, \nu)$. Regardless of the roles the firms take in this second transaction, we want their cultural proximity to remain constant, as the membership of cultural groups is fixed. This goal is achieved through the means of a symmetric proximity measure, and the Bhattacharyya coefficient complies with this symmetry requirement, as $BC(\nu, \omega) = BC(\omega, \nu)$.

Table 1: Effect of cultural proximity on trade, intensive and extensive margins

Dep. Variable	(1) Log Sales	(2) Log Transactions	(3) Log Sales	(4) Log Transactions	(5) Trade Indicator	(6) Trade Indicator
BC	0.100***	0.066**	0.129***	0.076***	0.0009***	0.0010***
	(0.033)	(0.027)	(0.034)	(0.028)	(0.0001)	(0.0001)
Log dist.	-0.023	-0.065***			0.0001	
	(0.015)	(0.011)			(0.0000)	
Obs.	32,678	32,678	32,843	32,843	5,606,627	5,628,290
Adj. R2	0.415	0.359	0.410	0.356	0.617	0.0106
FE	Seller, buyer	Seller, buyer	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.	Seller, buyer	Seller, buyer, origin×dest.

Notes: Columns 1, 2, 3 and 4 show the results of estimating Equation 1. Columns 5 and 6 show the results of estimating Equation 2. ***, ** and * indicate statistical significance at the 99, 95, and 90 percent levels respectively. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors are two-way clustered at the seller and buyer level. Standard errors in parentheses. The higher the Bhattacharyya coefficient, the culturally closer the two firms are. The number of observations varies between specifications due to the dropping of observations separated by a fixed effect (Correia et al., 2019).

We confirm the findings using a gravity equation. For transactions from firm ν to firm ω in our sample we estimate

$$\ln y(\nu, \omega) = \iota_\nu + \iota_\omega + \delta BC(\nu, \omega) + \eta \ln dist(\nu, \omega) + \varepsilon(\nu, \omega), \tag{1}$$

where $y(\nu, \omega)$ is either the total sales $n(\nu, \omega)$ or total transactions $t(\nu, \omega)$ from seller ν to buyer ω, $BC(\nu, \omega)$ is the Bhattacharyya coefficient, $dist(\nu, \omega)$ is the Euclidean distance between the pincodes in which the firms are located, ι_ν and ι_ω are seller and buyer fixed effects. Columns 1-4 of Table 1 present the results of the intensive margin estimation, which confirm the preliminary findings from Figure 3. Columns 1 and 2 show that, on average, there will be a higher amount of sales and transactions between a pair of firms when these firms are more alike in cultural terms. Columns 3 and 4 show that these results remain strong after including origin-destination fixed effects, which account for geographic distance but also control for other features that might arise between a pair of locations, such as different terrains, different languages, location-specific cultural ties, historical ties, etc.

Fact 2: Cultural proximity increases the likelihood of ever trading. Next, we estimate the extensive margin relationship. Given the size of our full dataset, the number of potential extensive margin links is computationally large. For tractability, we modify our sample. In the first place, we construct a sample with all possible combinations of in-state buyers and in-state sellers with cultural group information. Then, we proceed to drop all potential

transactions that include unfeasible sectoral combinations. That is, we drop the combinations of firms that are involved in productive sectors that never recorded a transaction in the data. Finally, we drop all unfeasible transactions based on distance. This is to say, we drop the combinations of firms where the seller is further away than the maximum recorded distance for the in-state buyer or vice versa.

Figure 4: Effect of cultural proximity on prices
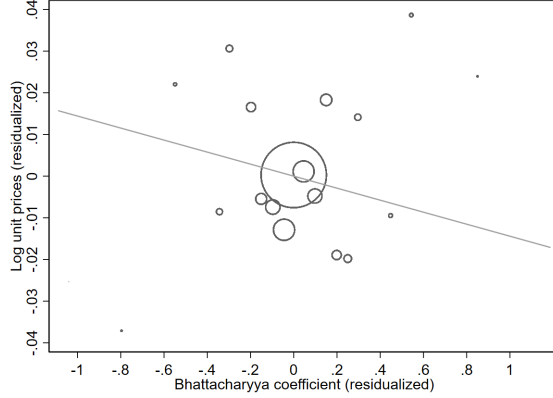
Notes: Results residualized of seller fixed effects and HS code fixed effects. Sectors are defined according to the 6-digit HS classification. Equally distanced bins formed over the horizontal axis. The size of the bubbles represents the number of transactions in each bin. The higher the Bhattacharyya coefficient, the culturally closer the two firms are.

With this sample, we construct a trade indicator variable $tr\left(\nu,\omega\right)$ which is equal to 1 if there is any kind of trade between firms ν and ω, and 0 otherwise. With this variable, we estimate a gravity-type specification:

$$tr\left(\nu,\omega\right) = \iota_\nu + \iota_\omega + \delta BC\left(\nu,\omega\right) + \eta \ln dist\left(\nu,\omega\right) + \varepsilon\left(\nu,\omega,t\right). \tag{2}$$

Columns 5-6 of Table 1 present the extensive margin results. We find that the higher the Bhattacharyya coefficient, the more likely it is that two given firms will trade.

Fact 3: Cultural proximity lowers prices. Figure 4 now uses buyer-seller-product-month groups and shows the residualized scatterplots between the similarity measure and the unit prices. We see the higher the Bhattacharyya coefficient between two firms involved in a transaction, the lower the price that will be charged. To confirm the results, we work with transaction-level data and estimate:

$$\ln p_g\left(\nu,\omega,t\right) = \iota_{\nu g} + \iota_{gt} + \iota_\omega + \delta BC\left(\nu,\omega\right) + \eta \ln dist\left(\nu,\omega\right) + \epsilon_g\left(\nu,\omega\right), \tag{3}$$

where $p_g(\nu, \omega, t)$ is the unit value of good g (at the 6-digit HS classification) sold by firm ν to firm ω in month t, $\iota_{\nu g}$ is a seller-good fixed effect and ι_{gt} is a good-month fixed effect. We present the results in Table 2, which confirms the previous findings from Figure 4: the culturally closer, the lower the unit value of the transactions.

Table 2: Effect of cultural proximity on prices

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Log Prices	Log Prices	Log Prices	Log Prices	Log Prices	Log Prices
BC	-0.069**	-0.069**	-0.066**	-0.045*	-0.040*	-0.039*
	(0.033)	(0.033)	(0.033)	(0.023)	(0.023)	(0.022)
Log dist.	0.023	0.023	0.028*			
	(0.016)	(0.016)	(0.017)			
Obs.	230,744	230,744	226,645	235,001	236,617	230,900
Adj. R2	0.932	0.932	0.935	0.933	0.925	0.936
FE	Seller×HS, buyer	Seller×HS, buyer, month	Seller×HS, buyer, month×HS	Seller×HS, buyer, origin×dest.	Seller×HS, buyer, month, origin×dest.	Seller×HS, buyer, month×HS, origin×dest.

Notes: This table shows the results of estimating Equation 3. Good g is defined according to 6-digit HS classification. Prices trimmed by 4-digit HS code at 5 and 95 percent. ***, ** and * indicate statistical significance at the 99, 95, and 90 percent levels, respectively. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors are multi-way clustered at the seller, 4-digit HS and origin-destination level. Standard errors are in parentheses. The higher the Bhattacharyya coefficient, the culturally closer the two firms are. The number of observations varies between specifications due to the dropping of observations separated by a fixed effect (Correia et al., 2019).

3.1 Mechanisms

3.1.1 Contracting frictions

Differentiated goods and contract enforcement. To understand the underlying forces driving these empirical patterns, we explore the role of cultural proximity in alleviating contracting frictions. The lack of contract enforcement in developing countries inhibits trade as sellers or buyers may not comply with the terms of the contract. For instance, the buyer could hold up the seller by withholding payment after the buyer receives the shipped goods. Differentiated or relationship-specific goods are subject to more severe hold-up problems, as there are fewer alternative buyers and sellers of such products, and buyers may withhold payment knowing that these goods are not useful outside of the relationship. In that sense, differentiated goods rely on better contract enforcement.

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Contract enforcement can be either formal (e.g. courts) or informal (e.g. cultural proximity). Most of the literature has focused on the role of formal institutions in enforcing contracts. We hypothesize and show evidence that cultural proximity alleviates contracting frictions for differentiated goods when formal contract enforcement is lacking (Nunn, 2007).

To bring in information about the type of product, we disaggregate our data at the transaction level. Then, we classify the goods into differentiated goods and non-differentiated goods based on the classification developed by Rauch (1999).[12] We estimate the following specification:

$$
\begin{aligned}
\ln n_g\left(\nu, \omega, t\right) = \quad & \iota_{\nu g} + \iota_{gt} + \iota_\omega + \delta BC\left(\nu, \omega\right) + \xi\left(BC\left(\nu, \omega\right) \times \mathbb{I}_g^{diff}\right) \\
& + \eta \ln dist\left(\nu, \omega\right) + \epsilon_g\left(\nu, \omega\right),
\end{aligned}
\tag{4}
$$

where $n_g\left(\nu, \omega, t\right)$ are the sales going from firm ν to firm ω of good g in month t and $\mathbb{I}_g^{diff}$ is an indicator for differentiated goods.[13] Columns 2 and 3 of Table 3 present the results. Our findings suggest that the baseline results of cultural proximity increasing trade are mostly driven by differentiated goods.

To understand the channel for why trade in differentiated goods depends on cultural proximity, we turn to the analysis of contract enforcement. We posit that, when facing poor contract enforcement and poor quality of institutions, firms trading differentiated goods must rely on alternative mechanisms that substitute the formal ones. Here, cultural proximity arises as a substitute for the trust and enforcement a well-functioning contract would have provided (Munshi, 2019, 2014).

To test this channel in our firm-to-firm setting, we use data from Ash et al. (2021), and calculate the average number of months between the filing of a case and its first hearing in each district court between 2010 and 2018. Intuitively, the longer the delays, the worse the contract enforcement. We estimate the following specification:

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[12]According to Rauch (1999) differentiated goods are the goods not traded in organized exchanges or not reference priced in commercial listings. Differentiated goods have specific characteristics that "differentiate" (i.e. specialized goods, branded goods) them from other, more homogeneous types of goods. Because of their relative uniqueness in features, these goods are not as easily replaceable as non-differentiated goods and, as such, rely more on relationship-specific types of trade. This means sellers and buyers must face search frictions to match to a suitable trade partner and will likely not abandon the commercial matches they have already made.

[13]We use both the conservative and liberal classifications from Rauch (1999). The conservative classification minimizes the number of goods classified as non-differentiated and, thus, has the largest amount of differentiated goods. The liberal classification maximizes the amount of goods classified as differentiated and has the largest number of differentiated goods.

Table 3: Effect of cultural proximity on trade by types of good, intensive margin

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Log Sales	Log Sales	Log Sales	Log Sales	Log Sales	Log Sales
BC	0.099***	0.018	0.039	0.069**	-0.019	0.013
	(0.031)	(0.050)	(0.040)	(0.027)	(0.048)	(0.038)
$BC \times \mathbb{I}_g^{diff,con}$		0.122**			0.139**	
		(0.058)			(0.059)	
$BC \times \mathbb{I}_g^{diff,lib}$			0.097**			0.095**
			(0.047)			(0.047)
Obs.	174,352	174,352	174,352	177,584	177,584	177,584
Adj. R2	0.852	0.852	0.852	0.853	0.853	0.853
FE	Seller×HS,	Seller×HS,	Seller×HS,	Seller×HS,	Seller×HS,	Seller×HS,
	buyer,	buyer,	buyer,	buyer,	buyer,	buyer,
	month×HS	month×HS	month×HS	month×HS,	month×HS,	month×HS,
				origin×dest.	origin×dest.	origin×dest.

Notes: This table shows the results of estimating Equation 4. ***, ** and * indicate statistical significance at the 99, 95, and 90 percent levels respectively. Good g is defined according to the 6-digit HS classification. Sales were trimmed by 4-digit HS code at 5 and 95 percent. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors are two-way clustered at the seller and 4-digit HS level. Standard errors in parentheses. The higher the Bhattacharyya coefficient, the more culturally closer two firms are. The number of observations varies between specifications due to the dropping of observations separated by a fixed effect (Correia et al., 2019). $\mathbb{I}_g^{diff,con}$ indicates the good g is a differentiated one according to the conservative classification of Rauch (1999). $\mathbb{I}_g^{diff,lib}$ indicates the good g is a differentiated one according to the liberal classification of Rauch (1999).

$$
\begin{aligned}
\ln n_g\left(\nu,\omega,t\right) = {} & \iota_{\nu g} + \iota_{gt} + \iota_\omega + \delta BC\left(\nu,\omega\right) + \xi_1\left(BC\left(\nu,\omega\right) \times \mathbb{I}^{court}\left(\nu,\omega\right)\right) + \eta \ln dist\left(\nu,\omega\right) \\
& + \xi_2\left(BC\left(\nu,\omega\right) \times \mathbb{I}^{court}\left(\nu,\omega\right) \times \mathbb{I}_g^{diff}\right) + \epsilon_g\left(\nu,\omega\right),
\end{aligned}
\tag{5}
$$

where $\mathbb{I}^{court}\left(\nu,\omega\right)$ is an indicator that equals 1, whenever the sum of the delays in the origin-district court, and the destination-district court is above the 75th percentile. That is, the variable indicates if a given transaction involves districts with poor contract enforcement.

Column 1 of Table 4 shows that, while cultural proximity is important for firm-to-firm trade overall, it is particularly relevant for those pairs of districts with low court quality. We interpret this as evidence that firms rely on cultural proximity as a source of trust in places where institutions do not work well.

Importantly, Columns 2 and 3 of Table 4 show that such an effect is primarily explained by differentiated goods. In those places where contract enforcement is poor, cultural proximity

Table 4: Effect of cultural proximity on trade interacted by court quality, intensive margin

	(1)	(2)	(3)
Dep. Variable	Log Sales	Log Sales	Log Sales
BC	0.051*	0.053**	0.053*
	(0.027)	(0.027)	(0.027)
$BC \times \mathbb{I}^{court}$	0.160*	0.033	0.002
	(0.094)	(0.117)	(0.114)
$BC \times \mathbb{I}^{court} \times \mathbb{I}_g^{diff,con}$		0.229*	
		(0.130)	
$BC \times \mathbb{I}^{court} \times \mathbb{I}_g^{diff,lib}$			0.273**
			(0.124)
Obs.	166,448	166,448	166,448
Adj. R2	0.851	0.851	0.851
FE	Seller×HS,	Seller×HS,	Seller×HS,
	buyer,	buyer,	buyer,
	month×HS	month×HS	month×HS

Notes: This table shows the results of estimating Equation 5. ***, ** and * indicate statistical significance at the 99, 95, and 90 percent levels respectively. Good g is defined according to 6-digit HS classification. Sales were trimmed by 4-digit HS code at 5 and 95 percent. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors are two-way clustered at the seller and 4-digit HS level. Standard errors are in parentheses. The higher the Bhattacharyya coefficient, the culturally closer the two firms are. The number of observations varies between specifications due to the dropping of observations separated by a fixed effect (Correia et al., 2019). $\mathbb{I}^{court}(\nu, \omega)$ indicates if the sum of the delays in the origin-district court and the destination-district court is above the 75th percentile. $\mathbb{I}_g^{diff,con}$ indicates the good g is a differentiated one according to the conservative classification of Rauch (1999). $\mathbb{I}_g^{diff,lib}$ indicates the good g is a differentiated one according to the liberal classification of Rauch (1999).

allows the transaction of the type of goods that rely the most on strong contracts and institutions. This provides evidence for our proposed explanation: Cultural proximity acts as an informal substitute for the trust that a well-functioning contract would provide, as argued by Nunn (2007).

Differentiated goods are branded and specific to certain producing firms. In a country with market imperfections, firms can easily renege on their commitments. This is particularly exacerbated in regions with poor court quality and low contract enforcement. Unlike homogeneous goods, firms in differentiated good markets are not easily replaceable. As a result, firms buying or selling differentiated goods will only trade with firms they know and trust, and perhaps are culturally close.[14] As we show, this is particularly exacerbated in areas where the court system is delayed and backed up.

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[14]This relates to Rauch (1999), who mentions that search frictions (i.e. having to look for a trustworthy supplier) are more important to the trade of differentiated goods than to the trade of non-differentiated goods.

Complexity. To further investigate how differentiated and complex products are particularly reliant on caste-based trade, we analyze how the cultural proximity results vary by the number of varieties of goods bought and sold by firms. We first count how many 4-digit HS codes a firm buys or sells. Table 5 presents the results for the intensive margin, following a modified version of Equation 1. In our specifications $varieties_\nu^{sold}$ and $varieties_\nu^{bought}$ refer to the number of varieties sold and bought by the seller, while $varieties_\omega^{sold}$ and $varieties_\omega^{bought}$ refer to the number of varieties sold and bought by the buyer.

The results point to the effects of cultural proximity on trade being stronger when firms buy and sell more varieties. Our interpretation of these findings is that firms that buy and sell more varieties of goods have to face more contracting frictions, caused by having to negotiate more contracts. Then, these firms, to minimize their load of contracting frictions, will rely more on trading with counterparts that they trust. Moreover, this explanation based on trust is compatible with the results related to differentiated goods and contract enforcement. In both cases, we posit that the intensity of trade is driven by trust between firms, to overcome market imperfections in India.

Cancellations. Our data is unique in that it records canceled transactions as well. Among the diverse reasons for which cultural proximity could affect trade, we can also study reneged contracts. In this section, we analyze whether it becomes more likely pairs of firms will cancel their transactions if they are far in cultural terms. We estimate the following specification:

$$\mathbb{I}_g^{cancel}(\nu, \omega, t) = \iota_{\nu g} + \iota_{gt} + \iota_\omega + \delta BC(\nu, \omega) + \eta \ln dist(\nu, \omega) + \epsilon_g(\nu, \omega, t), \qquad (6)$$

where $\mathbb{I}_g^{cancel}(\nu, \omega, t)$ is an indicator that says if there was at least one canceled transaction going from firm ν to firm ω of good g (at the 6-digit HS classification) in month t, $\iota_{\nu g}$ is a seller-good fixed effect, ι_{gt} is a good-month fixed effect and ι_ω is a seller-level fixed effect. Here, we control for the month of the year to account for macro events that could have caused widespread cancellations.

Table 6 presents the results. We find that the closer firms are in cultural terms, the less likely it is that there will be a cancellation. Here we must highlight that cancellations can occur for reasons other than reneged contracts.

3.1.2 Preference-based mechanisms and Discrimination.

Social hierarchies To investigate the importance of vertical hierarchies and discrimination across cultural groups, we study whether there are asymmetric effects in transactions in

Table 5: Effect of cultural proximity on trade by number of varieties, intensive margin

	(1)	(2)	(3)	(4)
Dep. Variable	Log Sales	Log Sales	Log Sales	Log Sales
BC	0.111***	0.090**	0.107***	0.097**
	(0.040)	(0.040)	(0.035)	(0.039)
$BC \times varieties_\nu^{sold}$	0.089			
	(0.126)			
$BC \times varieties_\nu^{bought}$		0.121		
		(0.084)		
$BC \times varieties_\omega^{sold}$			0.112**	
			(0.051)	
$BC \times varieties_\omega^{bought}$				0.068
				(0.043)
Obs.	32,843	32,843	32,843	32,843
Adj. R2	0.410	0.410	0.410	0.410
FE	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.

	(5)	(6)	(7)	(8)
Dep. Variable	Log Transactions	Log Transactions	Log Transactions	Log Transactions
BC	0.056*	0.030	0.056*	0.042
	(0.032)	(0.032)	(0.029)	(0.032)
$BC \times varieties_\nu^{sold}$	0.095			
	(0.105)			
$BC \times varieties_\nu^{bought}$		0.141**		
		(0.067)		
$BC \times varieties_\omega^{sold}$			0.104**	
			(0.042)	
$BC \times varieties_\omega^{bought}$				0.071**
				(0.036)
Obs.	32,843	32,843	32,843	32,843
Adj. R2	0.356	0.357	0.357	0.357
FE	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.

Notes: This table shows the results of estimating a modified version of Equation 1. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent levels respectively. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors are two-way clustered at the seller and buyer level. Standard errors in parentheses. The higher the Bhattacharyya coefficient, the culturally closer two firms are. $varieties_\nu^{sold}$ and $varieties_\nu^{bought}$ refer to the number of different HS codes at the 4-digit level sold and bought by the seller divided by 100, respectively. $varieties_\omega^{sold}$ and $varieties_\omega^{bought}$ refer to the number of different HS codes at the 4-digit level sold and bought by the buyer divided by 100, respectively.

Table 6: Cancellations

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable			Ever canceled (0/1)			
BC	-0.006*	-0.006*	-0.006*	-0.005*	-0.000	-0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Obs.	252,191	252,191	248,192	256,819	258,481	252,829
Adj. R2	0.102	0.102	0.110	0.102	0.0695	0.108
FE	Seller×HS, buyer	Seller×HS, buyer, month	Seller×HS, buyer, month×HS	Seller×HS, buyer, origin×dest.	Seller×HS, buyer, month, origin×dest.	Seller×HS, buyer, month×HS, origin×dest.

Notes: This table shows the results of estimating Equation 6 at the transaction level. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent levels respectively. Good g is defined according to 6-digit HS classification. Sales are trimmed by 4-digit HS code at 5 and 95 percent. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors are two-way clustered at the seller and 4-digit HS level. Standard errors are in parentheses. The higher the Bhattacharyya coefficient, the culturally closer firms are. The number of observations varies between specifications due to the dropping of observations separated by a fixed effect (Correia et al., 2019).

which one firm is placed higher than the other based on the Varna-based hierarchy. This is one way of testing for preference-based discrimination across the social hierarchy. We define the Varna or religion for which a firm has the highest probability of belonging to.[15] We do not find evidence that hierarchies (and preference-based discrimination) across social groups matter for our cultural proximity results.

We use of two different indicators: $\mathbb{I}_{\nu_H \omega_L}$ and $\mathbb{I}_{\nu_L \omega_H}$. The first one captures that the seller belongs to a higher hierarchy than the buyer. The second indicates the seller is placed below the buyer in the social hierarchy. We include these two indicators by interacting them with our measure of cultural proximity. Table 7 presents the results for the intensive and extensive margins. The baseline category is that both firms belong to the same hierarchy. First, we find the baseline coefficient is very similar to those of Table 1. Second, we find there is no additional effect of cultural proximity when firms are placed differently in the hierarchy. We conclude that strong asymmetric effects caused by vertical discrimination across cultural groups are unlikely. The effect of cultural proximity is similar, whether or not the firms trading belong to the same or different hierarchies.

Age of firms Preference-based discrimination is not profit maximizing, and is likely to lead to discriminating firms exiting the market. We follow Becker (1957) to analyze whether

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[15]While the Varna-based hierarchy only relates to the Hindu religion, we also place other religions in this hierarchy based on their income levels.

Table 7: Effect of cultural proximity on trade by vertical hierarchies, intensive and extensive margins

Dep. Variable	(1) Log Sales	(2) Log Transactions	(3) Log Sales	(4) Log Transactions	(5) Trade Indicator	(6) Trade Indicator
BC	0.099***	0.068**	0.129***	0.079***	0.0010***	0.0010***
	(0.034)	(0.028)	(0.035)	(0.029)	(0.0001)	(0.0001)
$BC \times \mathbb{I}_{\nu_H \omega_L}$	0.023	0.097	0.008	0.072	-0.0002	-0.0003
	(0.113)	(0.091)	(0.116)	(0.092)	(0.0003)	(0.0003)
$BC \times \mathbb{I}_{\nu_L \omega_H}$	0.045	-0.076	-0.027	-0.123	-0.0002	-0.0004
	(0.128)	(0.102)	(0.129)	(0.103)	(0.0002)	(0.0002)
Obs.	30,997	30,997	31,119	31,119	5,456,512	5,477,548
Adj. R2	0.418	0.360	0.412	0.357	0.614	0.0107
FE	Seller, buyer	Seller, buyer	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.	Seller, buyer	Seller, buyer, origin×dest.

Notes: Columns 1, 2, 3 and 4 show the results of estimating a modified version of Equation 1. Columns 5 and 6 show the results of estimating a modified version of Equation 2. ***, ** and * indicate statistical significance at the 99, 95, and 90 percent levels respectively. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors are two-way clustered at the seller and buyer level. Standard errors are in parentheses. The higher the Bhattacharyya coefficient, the culturally closer the two firms are. The number of observations varies between specifications due to the dropping of observations separated by a fixed effect (Correia et al., 2019). The subindex that accompanies ν denotes the hierarchical position of the seller, while the subindex that accompanies ω denotes the hierarchical position of the buyer. H denotes a higher position and L denotes a lower position. The baseline category is when both firms have the same hierarchical position.

taste-based discrimination is behind our main findings. If there is taste-based discrimination, then we should see that firms that sell to culturally close firms at lower prices are willing to forego profits because of their preferences. A consequence would be that these firms are more prone to go bankrupt.

For our empirical analysis, we leverage information on the establishment date from India-MART (the date on which a firm was established) and registration date from the tax authority (the data in which a firm obtained its permit to trade). If there is taste-based discrimination, then we should see older firms relying less on cultural proximity. This would mean that firms that had a preference for selling to firms culturally close to them eventually went bankrupt, while the survivors were those firms that did not show these preferences.

Table 8 shows the results for a modified version of the intensive margin regressions according to Equation 1. If there was taste-based discrimination, then the interaction between the measure of cultural proximity and age should have a negative coefficient. However, we find weak evidence for taste-based discrimination, such that we cannot conclude this is the reason

behind our results.

Table 8: Effect of cultural proximity after controlling for establishment age of sellers, intensive margin

Dep. Variable	(1) Log Sales	(2) Log Transactions	(3) Log Sales	(4) Log Transactions
A) IndiaMART				
BC	0.734**	0.489*	0.800**	0.479
	(0.355)	(0.296)	(0.371)	(0.311)
BC×Log age seller	-0.199*	-0.124	-0.207*	-0.122
	(0.111)	(0.090)	(0.112)	(0.091)
Obs.	6,334	6,334	5,859	5,859
Adj. R2	0.428	0.303	0.387	0.237
B) Tax Authority				
BC	0.164	0.217**	0.150	0.233**
	(0.115)	(0.094)	(0.116)	(0.097)
BC×Log age seller	-0.032	-0.076*	-0.016	-0.082**
	(0.050)	(0.041)	(0.050)	(0.041)
Obs.	18,268	18,268	18,810	18,810
Adj. R2	0.406	0.333	0.403	0.332
FE	Seller, buyer	Seller, buyer	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.

Notes: Columns 1, 2, 3 and 4 show the results of estimating a modified version of Equation 1. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent levels respectively. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors are two-way clustered at the seller and buyer level. Standard errors are in parentheses. The higher the Bhattacharyya coefficient, the culturally closer two firms are. Number of observations varies between specifications due to the dropping of observations separated by a fixed effect (Correia et al., 2019). In Panel A, the age of the seller comes from data reported in IndiaMART. In Panel B, the age of the seller comes from data reported by the tax authority.

3.2 Discussion of stylized facts

The stylized facts show that higher cultural proximity between a pair of firms favors trade in both the intensive and extensive margins, as well as lowers the price of the goods they trade. We discuss the possible mechanisms that may give rise to these findings.

Contracting frictions. In Section 3.1.1 we argue that contracting frictions could be the reason that drives the cultural proximity results. India is a country that suffers from a

severe lack of contract enforcement. *A priori*, a buyer may not know if the seller will deliver the goods under the agreed conditions (delivery, quality, etc.). Likewise, *a priori*, the seller may not know if the buyer will pay under the agreed conditions. This means buyers and sellers incur contracting frictions to find suitable trading partners (Boehm and Oberfield, 2020). Quantity-wise and matching-wise, this lowers trade as firms must pay a matching cost. Price-wise, this increases prices as the matching cost is passed down by the sellers to the aforementioned prices.

In this case, cultural proximity can work as a proxy for information and trust: culturally close firms may know and trust each other, and informally enforce contracts with social and reputational pressures. The higher the cultural proximity, the lower the contracting frictions. As a result, there would be more trade and lower prices, consistent with our previous findings. In Section 4.1, we present a simple theoretical framework in which cultural proximity affects contracting frictions and affects trade and prices. Our model suggests that if contracting frictions drive initial trade barriers, cultural proximity may reduce such frictions.

***Preference-based mechanisms* and discrimination.** We argue the results are unlikely to emerge from buyers having an inherent preference for buying from sellers culturally close to them. This preference would be a demand shifter that is active for those sellers that are close in cultural terms. While this would certainly increase the quantity traded, it would increase the price of traded goods, a result inconsistent with our previous findings.

The stylized facts can arise from having sellers that show a preference for selling to culturally close buyers. This would imply increased supply for those buyers who are culturally close to the seller. However, we do not find conclusive evidence of this channel.

Discrimination from high-caste cultural groups against low-caste cultural groups may again reduce trade. Yet, we find there is no additional effect of cultural proximity when firms are placed differently in the hierarchy. As such, we detect no asymmetric effects caused by vertical discrimination across cultural groups.

3.3   Robustness

We examine alternative specifications and heterogeneity in responses that shed light on various other channels in Appendix B.

Correction for selection bias.   Helpman et al. (2008) shows that the standard gravity equation estimations are biased as they do not account for selection issues. We follow their

suggested correction in Tables A2 and A3. As the correction mentions, we need an excluded instrument that affects only the extensive margin (i.e. the matching cost) and not the intensive margin (i.e. the trade cost). We consider the participation of both seller and buyer in the IndiaMART online B2B platform, under the idea that online platforms should reduce their matching costs. The results show that the coefficients are downward biased if we do not account for the selection issues. Therefore, our main results in the paper provide a lower bound on the effect that cultural proximity has on the intensive margin of trade.

Alternative cultural proximity measure. As an alternative to the Bhattacharyya coefficient, we perform estimation exercises using a symmetric version of the Kullback and Leibler (1951) divergence. Tables A4 and A5 show our baseline findings are robust to this alternative cultural proximity measure.

Language. We test whether the results we find are driven by linguistic similarity. To do so, we follow the two linguistic distance measures from Kone et al. (2018). Table A6 shows that language does not affect the cultural proximity results already established.

Goods specialization. Cultural groups in India are, in many cases, defined by the production of specific goods (Munshi, 2019).[16] Therefore, we analyze if the reason behind the cultural proximity results is cultural groups specializing in the production of certain goods and, given this, forming special bonds with their specific set of buyers. In Table A7 we do not find evidence of good specialization driving the results. This means that cultural proximity matters for all types of goods: for those in which a cultural group specializes and for those in which a cultural group does not specialize too.

Industry pair linkages. In the production matrix of an economy, some sectors are more likely to trade with others because of the nature of their activities. The same cultural group may happen to participate in the same industry. In Table A8, we present the results for the intensive margin after adding an industry of seller × industry of buyer fixed effect. We find that the result of there being more trade between culturally closes firms prevails.

4   Quantitative Importance of Cultural Proximity

In this section, we perform a counterfactual analysis to quantify the importance of cultural proximity for trade and welfare. First, we describe the model. Then, we describe how we estimate and calibrate the model. Finally, we perform three counterfactual scenarios. In

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[16]We can also understand this as certain cultural groups specializing in certain occupations.

particular, we show the importance of cultural proximity by implementing (i) social inclusion/mixing policies, (ii) social isolation policies, and (iii) reduction of contracting frictions.

4.1 Model

We build a quantitative inter-firm trade model and cultural differences between firm owners. We start with a static model, but allow firm owners to differ in their cultural endowments, which we then use to construct measures of cultural proximity. In this section, we briefly describe the model. For further details of the model, see Appendix C.

4.1.1 Preferences

A representative household demands goods with constant elasticity of substitution (CES) $\sigma > 1$ from an exogenous set of firms Ω, and inelastically supplies labor to firms. The household maximizes utility $\left(\int_{\omega \in \Omega} y(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}$ subject to its budget constraint $\int_{\omega \in \Omega} P(\omega) y(\omega) d\omega \leq Y$, where $y(\omega)$ is the household demand for good ω, $P(\omega)$ is the price the household pays for good ω, and Y is total income. This generates the demand function $x(\omega) = P(\omega)^{1-\sigma} P^{\sigma-1} Y$, where $x(\omega) \equiv P(\omega) y(\omega)$, and $P \equiv \left(\int_{\omega \in \Omega} P(\omega)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$ is a CES price index.

4.1.2 Technology

There is a continuum of firms that operate under monopolistic competition and produce differentiated goods indexed by ω. Since each firm produces a unique good, ω denotes a firm or a good. We consider a roundabout production economy, so firms can purchase intermediate inputs from all firms in the economy. Each firm produces its differentiated good with hired labor from the representative household and intermediate inputs.

Firms operate in three steps. First, sellers endogenously choose buyers (i.e. matching). In particular, a seller ν sells to buyer ω whenever the profits of doing so are larger than the fixed costs of matching $\epsilon F(\nu, \omega)$. Guided by our stylized facts, we argue that cultural proximity $BC(\nu, \omega)$ between seller ν and buyer ω determines the pairwise matching costs $F(\nu, \omega)$. Indeed, previous work describes how culture encodes information that is useful for sellers to decide which buyer to sell to (Allen et al., 2019; Balmaceda and Escobar, 2017).[17]

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[17]There could be other microfoundations motivating how culture influences matching costs (e.g. risk-sharing as in Ambrus et al. 2014; Bloch et al. 2008). These would generate similar frictions at the extensive and intensive margin.

Second, upon matching, due to the risk of buyers withholding payment, sellers charge a premium to buyers (i.e. terms of trade). In particular, the price that seller ν charges to buyer ω includes a premium $d(\nu, \omega) \geq 1$, which is a function of different factors that influence the hold-up process. Guided by our stylized facts, we posit that cultural proximity $BC(\nu, \omega)$ between seller ν and buyer ω determines $d(\nu, \omega)$. This is similar to earlier work on how culture can be an informal institutional channel to solve hold-up problems.[18] Third, sellers and buyers trade.

Step 1: Matching. In the first step, we endogenize sellers selecting which buyers to trade with by laying out the maximization problem of firms, and how cultural proximity influences it. A seller ν matches with buyer ω whenever the seller's profits of doing so $\pi(\nu, \omega)$ are larger than the fixed costs of matching $\epsilon F(\nu, \omega)$, where $F(\nu, \omega)$ are pairwise fixed costs of matching, and ϵ are i.i.d. log normal errors with mean $\mu_{\ln(\epsilon)}$ and standard deviation $\sigma_{\ln(\epsilon)}$.

To introduce the role of cultural proximity on the extensive margin of trade, we assume firms are *ex ante* heterogeneous in their cultural endowments. This captures the idea that a firm owner is born within a cultural setup that he inherits and then uses to interact with other firm owners. To match with our empirical section, we consider that each firm receives a vector of cultural endowments $\boldsymbol{\rho_\omega}$, so we can construct a measure of cultural proximity between firms ν and ω as $BC(\nu, \omega) = \sqrt{\boldsymbol{\rho_\nu \rho_\omega}}$.

In Appendix C we introduce a microfoundation on how $F(\nu, \omega)$ depend on $BC(\nu, \omega)$. In this microfoundation, sellers are looking for buyers, and vice-versa. Firms can meet costlessly, so all firms can meet each other before deciding who to match with. The purpose of a meeting is to infer the fixed costs the seller would incur if they were to trade with each buyer. Here we rationalize how sellers infer the costs of matching arising from cultural proximity. In particular, we consider an exponential function of fixed matching costs to cultural proximity, such that

$$F(\nu, \omega) = \kappa + \exp\left(-\gamma BC(\nu, \omega)\right), \tag{7}$$

where $\gamma > 0$ measures the sensitivity of the pairwise matching cost to the cultural proximity $BC(\nu, \omega)$, and κ is a scaling constant. The intuition behind parameter γ is that it captures institutional features, like court quality. In this sense, Table A1 in Appendix A suggests that parameter γ increases in magnitude when $\mathbb{I}^{court} = 1$ and firms face weak court quality. The lower the quality of courts is, the larger parameter γ is, and the more firms rely on cultural proximity to match.

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[18]Again, this would be consistent with other microfoundations on how culture influences trade costs due to reputation (Banerjee and Duflo, 2000; Chen and Wu, 2021) or loyalty (Board, 2011).

Step 2: Terms of the contract. After matching, seller ν and buyer ω set up the terms of the contract. We first consider the possibility that the buyer may withhold payment after the seller ships the goods. The seller's concerns around this issue can be monetized in the premium that the seller charges to the buyer. This premium gets passed to the unit price $p(\nu, \omega)$ that results from profit maximization $p(\nu, \omega) = \mu c(\nu) d(\nu, \omega)$, where $c(\nu)$ is the marginal cost and $\mu \equiv \frac{\sigma}{\sigma-1}$ is a markup.

In Appendix C we introduce a microfoundation on how $d(\nu, \omega)$ depend on $BC(\nu, \omega)$. In this microfoundation, $d(\nu, \omega)$ is proportional to the expected number of times buyer ω withholds payment to seller ν, which in turn is determined by cultural proximity $BC(\nu, \omega)$. We then obtain that the premium is

$$d(\nu, \omega) = \exp(\beta BC(\nu, \omega) + \epsilon(\nu, \omega)), \tag{8}$$

where $\beta < 0$ is a trade cost semi-elasticity, and $\epsilon(\nu, \omega)$ are unobservables. β depends on institutional features, like court quality. Based on the result of Table 4, we know model parameter β increases in magnitude when $\mathbb{I}^{court} = 1$ and firms face bad courts. As such, β relates to how firms respond to court quality: the lower the quality of the courts, the larger the magnitude of β, and the more important cultural proximity is for trade.

Step 3: Trade. Finally, we model trade. Each firm has a technology $y(\omega) = \kappa_\alpha z(\omega) l(\omega)^\alpha m(\omega)^{1-\alpha}$, where $y(\omega)$ is output, $\kappa_\alpha \equiv \frac{1}{\alpha^\alpha(1-\alpha)^{1-\alpha}}$ is a normalization constant, $z(\omega)$ is firm-level productivity, $l(\omega)$ is labor, and $m(\omega)$ are intermediate inputs from other firms. In turn, the intermediate inputs are defined as a CES composite, where $m(\omega) = \left(\int_{\nu \in \Omega(\omega)} m(\nu, \omega)^{\frac{\sigma-1}{\sigma}} d\nu\right)^{\frac{\sigma}{\sigma-1}}$, where $m(\nu, \omega)$ is quantity of inputs from seller ν to buyer ω, $\sigma > 1$ is the elasticity of substitution across intermediates, and $\Omega(\omega)$ is the endogenous set of suppliers of buyer ω.

By cost minimization, marginal costs are $c(\omega) = \frac{P(\omega)^{1-\alpha}}{z(\omega)}$, where $P(\omega) \equiv \left(\int_{\nu \in \Omega(\omega)} p(\nu, \omega)^{1-\sigma} d\nu\right)^{\frac{1}{1-\sigma}}$ is a CES price index across prices of intermediates, and labor is the numeraire good, so $w = 1$. Profit maximization subject to demand generates constant markup pricing such that the unit price is $p(\nu, \omega) = \mu c(\nu) d(\nu, \omega)$, as stated before.

Finally, we derive the demand of intermediates $n(\nu, \omega) = p(\nu, \omega)^{1-\sigma} P(\omega)^{\sigma-1} N(\omega)$, $N(\omega) = \int_{\nu \in \Omega(\omega)} n(\nu, \omega) d\nu$ is the total intermediate purchases by buyer ω and $n(\nu, \omega) \equiv p(\nu, \omega) m(\nu, \omega)$ is the value of purchases from seller ν to buyer ω.

From the demand of intermediates and firm pricing, we can obtain the gravity equation as

$$\log(n(\nu, \omega)) = \iota_\nu + \iota_\omega + (1 - \sigma) \log(d(\nu, \omega)), \tag{9}$$

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where ι_ν and ι_ω are seller and buyer fixed effects, also known as *multilateral resistance terms*. Here, the premium $d(\nu, \omega)$ enters the gravity equation as a trade cost. This gravity equation relates directly to Equation 1 that we estimate.

4.2 Estimation and calibration

Here we explain how we estimate the key parameters of the model on cultural endowments, (intensive) trade costs, and seller matching costs. We also describe how we calibrate the remaining parameters of the model.

Cultural endowments ρ. For the cultural endowments, we assume each firm ν has a probability vector $\boldsymbol{\rho_\nu} = [\rho_\nu(1), \ldots, \rho_\nu(452)]$ of belonging to each of the 452 cultural groups, we observe in the data. We further assume the elements of $\boldsymbol{\rho_\nu}$ are randomly drawn from a Dirichlet distribution, such that $\rho_\nu(1), \ldots, \rho_\nu(452) \sim \mathcal{D}(\alpha_1, \ldots, \alpha_{452})$, where $\alpha_1, \ldots, \alpha_{452} > 0$ are concentration parameters.[19] The probability density for the Dirichlet distribution is

$$\rho_\nu(1), \ldots, \rho_\nu(452) \sim \mathcal{D}(\alpha_1, \ldots, \alpha_{452}) = \frac{\Gamma\left(\sum_{x=1}^{452} \alpha_x\right)}{\prod_{x=1}^{452} \Gamma(\alpha_x)} \prod_{k=1}^{452} \rho_\nu(x)^{\alpha_x - 1},$$

such that $\rho_\nu(x) \in [0, 1]$, $\sum_{x=1}^{452} \rho_\nu(x) = 1$, where $\Gamma(.)$ is the gamma function and $\frac{\Gamma\left(\sum_{x=1}^{452} \alpha_x\right)}{\prod_{x=1}^{452} \Gamma(\alpha_x)}$ is a normalization constant. To ensure the theoretical Dirichlet distribution produces draws that are similar to the probabilities we see in the data, we estimate the vector $\boldsymbol{\alpha} = \begin{bmatrix} \alpha_1, & \ldots, & \alpha_{452} \end{bmatrix}$ parameters by maximum likelihood.[20] Let $\boldsymbol{\varrho} = \{\boldsymbol{\rho_1}, \ldots, \boldsymbol{\rho_N}\}$, where $\mathcal{N}$ is the total number of firms. Then, the log-likelihood function is

$$\ln pr(\boldsymbol{\varrho}|\boldsymbol{\alpha}) = \mathcal{N} \ln \Gamma\left(\sum_{x=1}^{452} \alpha_x\right) - \mathcal{N} \sum_{x=1}^{452} \ln \Gamma(\alpha_x) + \mathcal{N} \sum_{x=1}^{452} (\alpha_x - 1) \left(\frac{1}{\mathcal{N}} \sum_{\nu=1}^{\mathcal{N}} \ln \rho_\nu(x)\right). \quad (10)$$

Trade costs d. From Equation 8 we need an estimate for $\{\beta_1, \beta_2\}$. Our setup produces a clear empirical counterpart that we already estimated in the reduced-form section, conditional on high-dimensional fixed effects. So we obtain estimates for these two parameters by linking the theoretical gravity Equation 9 to the empirical gravity equation results (Column 1 from Table 1). Thus, we obtain $\{\beta_1, \beta_2\} = \{0, -0.03\}$.[21]

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[19] For a given x, the higher this parameter, the more disperse the realizations of $\rho_\nu(x)$ are across firms ν.

[20] For this, we use the Matlab toolboxes `fastfit` and `lightspeed` by Tom Minka. We present the estimated parameters in Figure A1 in Appendix A.

[21] Even though the wedge also appears in the price Equation A8 of the model, we do not estimate this equation to identify β_1 and β_2. The reason is that the price equation is not an equilibrium equation, while

Matching cost F. From Equation 7, we need an estimate for γ. We do this in two steps. First, using the extensive margin sample we run the following estimation

$$\ln\left[n\left(z,z'\right)\right] = \iota_z + \iota_{z'} + \delta BC\left(z,z'\right) + \eta\ln\left(dist\left(z,z'\right)\right) + \varepsilon\left(z,z'\right), \tag{11}$$

where we apply the inverse hyperbolic sine transformation to the dependent variable, so as to not lose the cases in which there is zero trade. With this, we recover

$$\ln\widehat{\left[n\left(z,z'\right)\right]} = \widehat{\iota}_z + \widehat{\iota}_{z'} + \widehat{\delta}BC\left(z,z'\right) + \widehat{\eta}\ln\left(dist\left(z,z'\right)\right),$$

where the hats denote estimated parameters and $\ln\widehat{[n(z,z')]}$ are the predicted sales. This variable predicts what would be the sales for a pair of seller and buyer even in the case they did not actually trade in the data. Second, we combine and rearrange Equations (A7) and (7), such that

$$l\left(z,z'\right) = \int 1\left[\ln\left(\epsilon\left(z,z'\right)\right) < \ln\widehat{[n(z,z')]} - \ln\left(\sigma\right) - \gamma BC\left(z,z'\right)\right] dH\left(\epsilon\left(z,z'\right)\right), \tag{12}$$

where we use the fact that $\pi\left(z,z'\right) = \frac{n\left(z,z'\right)}{\sigma}$ and replace $\ln\left[n\left(z,z'\right)\right]$ by its estimated counterpart $\ln\widehat{[n(z,z')]}$.[22] We estimate this last equation with a probit (assuming $\epsilon\left(z,z'\right)$ is log-normally distributed). We find that $\gamma = -0.13$, and statistically different from 0.[23]

Calibrated parameters and SMM. We calibrate the labor cost share $\alpha = 0.52$, the value reported for India for 2019 from the Penn World Tables (Feenstra et al., 2015). This value also considers the informal sector, which plays a large role in India. For the markup we use $\mu = 1.34$, which is the median markup across all Indian sectors reported by De Loecker et al. (2016). This markup implies an elasticity of substitution across suppliers $\sigma = 3.94$. Following Bernard et al. (2022) we normalize the total number of workers $L = 1$, take the nominal wage as the numeraire so $w = 1$, and set the total number of firms $\mathcal{N} = 400$.

For the log-productivity distribution, we assume a mean $\mu_{\ln(z)} = 0$. The remaining parameters are (i) the standard deviation of the log-productivity distribution $\sigma_{\ln(z)}$ and (ii) the mean $\mu_{\ln(\epsilon)}$, (iii) the standard deviation $\sigma_{\ln(\epsilon)}$ of the link function noise distribution and (iv)

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the gravity equation is. Also, for our simulations we add a constant to the trade cost, such that the minimum trade cost is equal to 1. Therefore, in our simulations we have $d\left(\nu,\omega\right) = \exp\left(-\beta_2 + \beta_2 BC\left(\nu,\omega\right)\right)$.

[22]For these estimations we ignore the scaling constant κ that appears in Equation 7.

[23]We present the results of the estimation in Table A1 in Appendix A. Also, for our simulations we add a constant to the matching cost, such that the minimum matching cost is equal to κ. Therefore, in our simulations we have $F\left(z,z'\right) = \kappa + \exp\left(-\gamma + \gamma BC\left(z,z'\right)\right)$.

the scaling constant for the pairwise matching cost κ. We estimate these four parameters so as to match targeted moments from the data, using a simulated method of moments (SMM). We explain this procedure below.

In Appendix E, we describe details on the targeted and untargeted moments we use. We show that, when it comes to the targeted moments, the model can very closely replicate the empirical ones. For the untargeted moments, the model gets reasonably close to the data.

4.3 Counterfactual analysis

We now present the results of various counterfactual exercises. First, we evaluate the effects of social mixing/inclusion and isolation policies, whereby we change the cultural proximity between firms (in our model terms, changing $BC\left(z, z'\right)$). Second, we study the effects of a policy that reduces contracting frictions, such that firms rely less on cultural proximity when trading (in terms of our model, shrinking parameters β_2 and γ).

To evaluate each scenario, we measure what happens to various model-based statistics. Welfare is measured by real wage, $\mathcal{W} = \frac{w}{P}$. To quantify the impact on aggregate productivity, we consider a sales-weighted average productivity measure such that $\mathcal{Z} = \left(\sum_{\nu=1}^{N} \phi_\nu z_\nu^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$, where ϕ_ν represents the proportion of the sales of firm ν over the total sales of the economy.

To analyze the impact on the total economic activity, we measure total sales $\mathcal{S} = \sum_{\nu=1}^{N} S_\nu$, where S_ν are the total sales of firm ν. Additionally, we consider the average normalized intermediate sales $mean\left[\ln\left(\widetilde{N}\left(\nu\right)/\mathcal{N}_b\left(\nu\right)\right)\right]$, where $\widetilde{N}\left(\nu\right)$ are the total intermediate sales of seller ν, and the average normalized intermediate purchases $mean\left[\ln\left(N\left(\omega\right)/\mathcal{N}_s\left(\omega\right)\right)\right]$.

For the prices, we compare the changes in the aggregate price index P. Finally, to study how matching between firms is affected, we present the results for the average normalized number of buyers, $mean\left[\ln\left(\frac{\mathcal{N}_b(\nu)}{\mathcal{N}}\right)\right]$, and the average normalized number of sellers, $mean\left[\ln\left(\frac{\mathcal{N}_s(\omega)}{\mathcal{N}}\right)\right]$.[24]

Social inclusion and social mixing policies. We analyze the effects of social inclusion/mixing policies. There is an important literature on the role of social cohesion for economic development (Alesina and Giuliano, 2015; Alesina and Reich, 2015; Bazzi et al., 2019; Depetris-Chauvin et al., 2020; Gradstein and Justman, 2019; Ritzen et al., 2000). We tie our counterfactuals to the importance of implementing affirmative action policies with the intention of

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[24]In contrast to the previous sections, in this part we define the aggregate measures discretely. This is due to the simulations having a discrete number of firms, rather than a continuum.

increasing cultural proximity (Alan et al., 2021; Alesina et al., 2021), particularly for India (Khanna, 2020; Munshi, 2019). For instance, affirmative actions programs may help incentivize students from different cultural groups to attend the same educative institutions. If these students then go on to become owners of the firms in the future, such policies may increase cultural proximity between firms, despite the fact the owners originally belonged to different cultural groups. Similarly, affirmative action in public sector jobs may also increase connections across caste lines, as individuals from different castes now work together.

To analyze the maximum potential of this policy within our theoretical framework, we propose case Counterfactual 1 (CF1), in which all the firms belong to the same cultural group. That is, we go from the baseline to $BC\left(z, z^{'}\right) = 1$ for all $z, z^{'}$, which makes the firms become the closest possible in cultural terms. In this scenario, there are no contracting frictions, as firms know and/or trust each other, and so they pay the minimum trade and matching costs.

Table 9 shows how the model statistics change in each counterfactual to the baseline. In case CF1, we have that firms become the closest in cultural terms, so trade costs and matching costs go to their minimum possible. Aligned with our empirical facts, with lower trade costs, total sales increase by 2.76 percent, while the average intermediate sales and purchases go up by 1.52 percent and 1.15 percent, respectively. With the lower matching costs the average number of buyers also increases. Also, because there are lower trade and matching costs, aggregate prices fall by 1.73 percent, and welfare increases by 1.76 percent.

Besides welfare, another aggregate measure we analyze is average productivity, which falls by 0.13 percent. Yet, average productivity masks substantial compositional changes, as these results depend on whether the less productive firms are selling more or less to the baseline case. We show in Table 10 that, in case CF1, when trade and matching costs decrease, the less productive firms match more and sell more, which increases their weight in the aggregate and lowers average productivity.

Social isolation policies. Since the rise of democracy, efforts have been put in place by the Indian government to end the influence of the caste system in the modern economy (Iyer et al., 2013; Munshi, 2019). What would have happened if sociopolitical forces perpetuated the social stratification of the caste system? To analyze the maximum impact of social isolation policies we propose case Counterfactual 2 (CF2), where we examine an extreme case in which each firm belongs to its own cultural group. Thus, we have a case where $BC\left(z, z^{'}\right) = 0$ for all $z, z^{'}$ and $z \neq z^{'}$, which makes the firms the furthest possible in cultural terms. Under this scenario, firms incur the maximum contracting frictions, for which they pay the maximum trade cost and the maximum matching cost.

Table 9: Effect of cultural proximity on aggregate outcomes (counterfactual scenarios)

	CF1: Social inclusion/mixing	CF2: Social isolation	CF3: Reducing contracting frictions
Welfare	1.76	-1.45	0.87
Ave. productivity	-0.13	0.10	-0.06
Total sales	2.76	-2.23	1.37
Ave. normalized intermediate sales	1.52	-1.20	0.76
Ave. normalized intermediate purchases	1.15	-0.94	0.57
Ave. normalized number of buyers	1.07	-0.87	0.53
Ave. normalized number of sellers	1.00	-0.82	0.50
Agg. price index	-1.73	1.47	-0.87

Notes: We present the percentage gains or losses to the baseline scenario. CF1 is a case where all the firms belong to the same cultural group. This is, we go from the baseline to $BC\left(z, z^{'}\right) = 1$ for all $z, z^{'}$, which makes the firms to become the closest possible in cultural terms. In this scenario, there are no contracting frictions, as firms know and/or trust each other, and so they pay the minimum trade and matching costs. CF2 is a case where each firm belongs to its own cultural group. Thus, we have a case where $BC\left(z, z^{'}\right) = 0$ for all $z, z^{'}$ and $z \neq z^{'}$, which makes the firms the furthest possible in cultural terms. Under this scenario, firms incur the maximum contracting frictions, for which they pay the maximum trade cost and the maximum matching cost. CF3 is a scenario where trade and matching costs become less sensitive to cultural proximity. In this case parameters β_2 and γ shrink by 50 percent.

Table 10: Change in sales by productivity quartiles

	CF1: Social inclusion/mixing	CF2: Social isolation	CF3: Reducing contracting frictions
1st quartile (most productive)	2.73	-2.21	1.35
2nd quartile	2.91	-2.35	1.44
3rd quartile	2.91	-2.31	1.44
4th quartile (least productive)	2.86	-2.32	1.42

Notes: We aggregate the sales of all firms that belong to a productivity quartile and calculate their percentage variation to the baseline. CF1 is a case where all the firms belong to the same cultural group. This is, we go from the baseline to $BC\left(z, z^{'}\right) = 1$ for all $z, z^{'}$, which makes the firms to become the closest possible in cultural terms. In this scenario, there are no contracting frictions, as firms know and/or trust each other, and so they pay the minimum trade and matching costs. CF2 is a case where each firm belongs to its own cultural group. Thus, we have a case where $BC\left(z, z^{'}\right) = 0$ for all $z, z^{'}$ and $z \neq z^{'}$, which makes the firms the furthest possible in cultural terms. Under this scenario, firms incur the maximum contracting frictions, for which they pay the maximum trade cost and the maximum matching cost. CF3 is a scenario where trade and matching costs become less sensitive to cultural proximity. In this case parameters β_2 and γ shrink by 50 percent.

When all firms are the furthest in cultural terms, trade costs and matching costs are the

highest. Table 9 shows that in case CF2 total sales fall by 2.23 percent, and prices increase by 1.47 percent. Average intermediate sales and purchases also fall. There are also fewer matches, and the average number of buyers and sellers falls by at least 0.82 percentage points. As a result, welfare falls by 1.45 percent. Average productivity increases by 0.10 percent, relative to the baseline. Table 10 shows that with social isolation, every firm loses in terms of sales. However, the firms that lose the most are the least productive, which shrinks their weight in the aggregate and, thus, drives average productivity up.

Reducing contracting frictions. Now we turn to study which would be the effect of reducing contracting frictions. A policy that improves the quality of courts would reduce the contracting frictions firms face. In terms of our framework, this means that the trade cost and the matching cost become less sensitive to our measure of cultural proximity. Thus, in the Counterfactual 3 (CF3) we analyze a case where parameters β_2 and γ shrink by 50 percent. This captures how reducing contracting frictions affects aggregate outcomes via the channel of trade becoming less reliant on cultural proximity.[25]

Table 9 shows that after reducing contracting frictions in case CF3, total sales rise by 1.37 percent, and prices fall by 0.87 percent. Average intermediate sales and purchases increase. The number of matches also increases, with the average number of buyers and sellers rising by about 0.5 percent. Welfare increases by 0.87 percent, and average productivity falls by 0.06 percent. In Table 10 we show that in reducing contracting frictions, all firms gain in terms of sales to the baseline. Nonetheless, it is the less productive firms that gain the most, such that their weight in the aggregate increases. This drives the average productivity down.

5 Conclusions

We shed light on how cultural proximity shapes the formation of production networks and its implications for welfare. We first provide empirical evidence on the role of cultural proximity for inter-firm trade by leveraging a new dataset of firm-to-firm transactions from a large Indian state, along with data on firm owner names and their cultural proximity derived from India's caste and religious system.

We report three new stylized facts. First, culturally closer firms report higher sales between them, on the intensive margin. Second, culturally closer firms are more likely to ever trade

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[25]Reducing contracting frictions may affect aggregate outcomes through other channels as well, such as more investments in differentiated products, and more trade across longer distances.

with each other, on the extensive margin. Third, firms that are culturally further apart report higher unit prices in their transactions.

We explore various mechanisms and find evidence most consistent with the importance of alleviating contracting frictions. We do not find sufficient evidence that hierarchies (and preference-based discrimination) matter, or that linguistic distance and the specialization in certain goods matter for our results. We show evidence that suggests that the effect we find of cultural proximity on trade is stronger for differentiated goods, which often rely on either formal or informal contract enforcement (Nunn, 2007; Rauch, 1999). We also find that the importance of cultural proximity is elevated in regions with poor court quality (and so worse contract enforcement). Indeed, consistent with our narrative, the importance of court quality is only seen in trades of differentiated products, rather than homogeneous goods. We understand these results as evidence that cultural proximity is an informal mechanism that substitutes formal contract enforcement (Munshi, 2014, 2019).

We then build a quantitative general equilibrium model of firm-to-firm trade and cultural proximity. We introduce our measure of cultural proximity as a wedge that affects trade and matching costs, and estimate the key parameters of the model: the semi-elasticity of the trade cost to cultural proximity and the semi-elasticity of matching cost to cultural proximity. The model generates estimable specifications, that we take directly to the data. We use the estimated parameters to quantify the implications for welfare and other model-based statistics of implementing different policies. Welfare increases by 1.76 percent under social inclusion policies, falls by 1.45 percent under social isolation, and increases by 0.87 percent when reducing contracting frictions makes firms less reliant on cultural proximity.

In contexts like India, cultural and social networks may be used informally to overcome the lack of formal institutions that uphold contracts. Our paper is among the first to establish the consequences of these cultural ties in the context of trade. We study how social relationships influence firm-level decisions and quantify their importance for welfare. Our results have strong implications for policy. Promoting social inclusion and mixing via diversity-friendly policies can help facilitate matches and trade, with substantial implications for aggregate output and welfare. Furthermore, investing in reducing contracting frictions will allow firms to not have to rely on cultural ties, facilitating matches with more productive and low-cost suppliers, and once again improving economic well-being.

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A   Additional figures and tables

Figure A1: Histogram of estimated concentration parameters for Dirichlet distribution
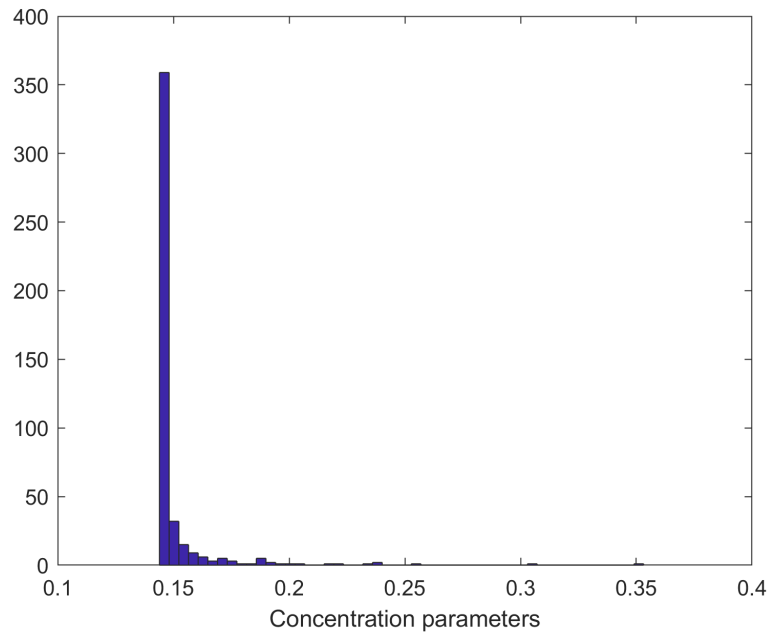
Notes: Estimated concentration parameters for a Dirichlet distribution according to the maximum likelihood estimation from Equation 10.

Table A1: Estimation for matching cost

	(1)	(2)
	1st Stage	2nd Stage
Dep. Variable	Sales (Hyperbolic Inverse Sine)	Trade Indicator
BC	0.013***	0.131***
	(0.001)	(0.008)
ihs $\widehat{[n(z,z')]}$		8.340***
		(0.024)
Obs.	5,606,627	5,606,627
Adj. R2	0.595	-
Pseudo R2	-	0.453
FE	Seller, buyer	-

Notes: Column 1 shows the results of estimating Equation 11. Column 2 shows the results of estimating Equation 12. We winsorize $\ln \widehat{n(z,z')}$ at 1 percent and 99 percent. Sample only contains in-state firms. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent levels respectively. Standard errors are clustered at the seller and buyer level in Column 1. Standard errors are in parentheses. The higher the Bhattacharyya coefficient, the culturally closer two firms are.

B Robustness

B.1 Correction for selection bias

Helpman et al. (2008) suggest that the traditional gravity equation estimations, which we use for our intensive margin regressions, are biased because of selection issues. Thus, in this section, we follow their proposed correction for selection bias.

In the first stage, we estimate the following linear probability model:

$$tr(\nu, \omega) = \iota_\nu + \iota_\omega + \delta BC(\nu, \omega) + \eta \ln dist(\nu, \omega) + \gamma B2B(\nu, \omega) + \epsilon(\nu, \omega), \qquad \text{(A1)}$$

where we follow the nomenclature and the in-state sample from our extensive margin regressions. Here, we need an excluded instrument that affects only the extensive margin (i.e. the matching cost) and not the intensive margin (i.e. the trade cost). Thus, we consider the indicator variable $B2B(\nu, \omega)$ that equals 1 when both seller ν and buyer ω are in IndiaMART and equals 0 otherwise. As mentioned in Section 2.2, IndiaMART is the largest e-commerce platform for business-to-business (B2B) transactions in India.[26] Thus, the idea here is that it is easier for both firms to match if they take part in this platform.

We present the results of this first stage in Table A2. As before, the closer the firms are in cultural terms, the more likely it is they will trade. Additionally, if both firms participate in IndiaMART, the more likely the trade.

After the estimation, we recover the predicted probability of trading $\widehat{tr}(\nu, \omega)$, with which we calculate the latent variable

$$\widehat{\zeta}(\nu, \omega) = \Phi^{-1}\left(\widehat{tr}(\nu, \omega)\right),$$

where $\Phi^{-1}(\cdot)$ is the inverse CDF of the standard normal distribution.

Following Heckman (1979), we obtain the inverse Mills ratio

$$\Upsilon\left(\widehat{\zeta}\right) = \frac{\phi\left(\widehat{\zeta}(\nu, \omega)\right)}{\Phi\left(\widehat{\zeta}(\nu, \omega)\right)},$$

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[26]In 2019, there were between 5 and 6 million registered firms in IndiaMART (https://www.indiamart.com), which represented all firm size groups and all geographic regions in India.

where $\phi(\cdot)$ is the PDF of the standard normal distribution, and $\Phi(\cdot)$ is the CDF of the standard normal distribution.

For the second stage, we estimate

$$\ln y(\nu,\omega) = \iota_\nu + \iota_\omega + \delta BC(\nu,\omega) + \eta \ln dist(\nu,\omega) + \upsilon \Upsilon\left(\widehat{\zeta}\right) + \epsilon(\nu,\omega), \qquad \text{(A2)}$$

where $y(\nu,\omega)$ is the total positive sales of seller ν to buyer ω and the term $\Upsilon\left(\widehat{\zeta}\right)$ accounts for selection bias.

We present the second stage results in Columns 3 and 4 of Table A3. We must note that for computational reasons, we work with only an in-state sample, our results are not directly comparable to the baseline results from Table 1. Therefore, Columns 1 and 2 present the results with the in-state sample but without the correction for selection bias.

We find that not considering the correction for selection biases the coefficients downwards. This way, we conclude that the main results related to the intensive margin in the paper represent a lower bound of the effect of cultural proximity on trade.

Table A2: Correction for selection bias, first stage

Dep. Variable	Trade Dummy
BC	0.0010***
	(0.0001)
$B2B$	0.0016***
	(0.0003)
Obs.	5,628,290
Adj. R2	0.0106
FE	Seller, buyer, origin×dest.

Notes: Table shows the results of estimating Equation A1. The sample contains only in-state firms. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent levels respectively. Standard errors are two-way clustered at the seller and buyer level. Standard errors are in parentheses. The higher the Bhattacharyya coefficient, the culturally closer two firms are.

B.2 Alternative cultural proximity measure

In this section, we present an alternative measure of cultural proximity to that of the Bhattacharyya coefficient. Define the standard discrete distribution-based Kullback and Leibler

Table A3: Correction for selection bias, second stage

Dep. Variable	(1) Log Sales	(2) Log Transactions	(3) Log Sales	(4) Log Transactions
BC	0.148***	0.095***	0.223***	0.132**
	(0.035)	(0.029)	(0.074)	(0.055)
Inv. Mills rat.			0.503	0.246
			(0.421)	(0.298)
Obs.	26,238	26,238	26,238	26,238
Adj. R2	0.392	0.360	0.392	0.360
FE	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.

Notes: Columns 1, 2, 3 and 4 show the results of estimating Equation A2. Columns 1 and 2 do not consider the correction for selection bias term. The sample contains only in-state firms. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent levels respectively. Standard errors are two-way clustered at the seller and buyer level. Standard errors are in parentheses. The higher the Bhattacharyya coefficient, the culturally closer two firms are. Number of observations varies between specifications due to the dropping of observations separated by a fixed effect (Correia et al., 2019).

(1951) divergence as

$$KL\left(\nu\|\omega\right) = \sum_{x=1}^{X} \rho_\nu\left(x\right)\log\left(\frac{\rho_\nu\left(x\right)}{\rho_\omega\left(x\right)}\right).$$

We have that $KL\left(\nu\|\omega\right) \geq 0$, where $KL\left(\nu\|\omega\right) = 0$ when sellers and buyers have exactly equal probability distributions, while it will be higher the more different the two probability distributions are.[27] Intuitively, we can see this measure as the expected difference between two probability distributions. However, this proximity measure is not symmetric; that is, $KL\left(\nu\|\omega\right) \neq KL\left(\omega\|\nu\right)$. Consider our previous example where we record a transaction between a seller ν and a buyer with distribution ω, from which we calculate $KL\left(\nu\|\omega\right)$. If, in a second transaction, the roles of the firms revert, then the Kullback-Leibler divergence would be $KL\left(\omega\|\nu\right)$, implying the cultural proximity between the two firms has changed, when it should not change. To convert this measure into a symmetric one, we define

$$KL_{sym}\left(\nu\|\omega\right) = KL\left(\nu\|\omega\right) + KL\left(\omega\|\nu\right) = KL_{sym}\left(\omega\|\nu\right).$$

Notice this similarity measure needs $\rho_\nu\left(x\right) > 0$ and $\rho_\omega\left(x\right) > 0$ for all x. However, the probability of a firm belonging to a certain cultural group may be zero. In those cases, we replace that probability of zero for a probability $\varepsilon \to 0^+$ such that KL_{sym} is well-defined.

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[27]This interpretation diverts from the standard use the Kullback-Leibler has in information theory, where a higher divergence means a higher information loss.

Tables A4 and A5 show the regression results for the intensive margin, extensive margin, and unit prices. In this case, the higher the Kullback-Leibler divergence, the more culturally different the buyer from the seller. The results confirm the findings from the main text.

Table A4: Effect of cultural proximity on trade, intensive and extensive margins, Kullback-Leibler

Dep. Variable	(1) Log Sales	(2) Log Transactions	(3) Log Sales	(4) Log Transactions	(5) Trade Indicator	(6) Trade Indicator
KL_{sym}	-0.004***	-0.003**	-0.005***	-0.003**	-0.00004***	-0.00004***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.00000)	(0.00000)
Log dist.	-0.023	-0.065***			0.00007	
	(0.015)	(0.011)			(0.00005)	
Obs.	32,678	32,678	32,843	32,843	5,606,627	5,628,290
Adj. R2	0.415	0.359	0.410	0.356	0.617	0.0106
FE	Seller, buyer	Seller, buyer	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.	Seller, buyer	Seller, buyer, origin×dest.

Notes: Columns 1, 2, 3 and 4 show the results of estimating a modified version of Equation 1. Columns 5 and 6 show the results of estimating a modified version of Equation 2. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent levels respectively. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors are two-way clustered at the seller and buyer level. Standard errors are in parentheses. A higher Kullback-Leibler divergence means two firms are socially farther away. Number of observations varies between specifications due to the dropping of observations separated by a fixed effect (Correia et al., 2019).

Table A5: Effect of cultural proximity on prices, Kullback-Leibler

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Log Prices	Log Prices	Log Prices	Log Prices	Log Prices	Log Prices
KL_{sym}	0.003**	0.003**	0.003**	0.002*	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log dist.	0.023	0.023	0.028*			
	(0.016)	(0.016)	(0.017)			
Obs.	230,744	230,744	226,645	235,001	236,617	230,900
Adj. R2	0.932	0.932	0.935	0.933	0.925	0.936
FE	Seller×HS, buyer	Seller×HS, buyer, month	Seller×HS, buyer, month×HS	Seller×HS, buyer, origin×dest.	Seller×HS, buyer, month, origin×dest.	Seller×HS, buyer, month×HS, origin×dest.

Notes: This table shows the results of estimating a modified version of Equation 3. Good g is defined according to 6-digit HS classification. Prices trimmed by 4-digit HS code at 5 and 95 percent. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent levels respectively. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors are multi-way clustered at the seller, 4-digit HS and origin-destination level. Standard errors are in parentheses. A higher Kullback-Leibler divergence means two firms are culturally farther away. Number of observations varies between specifications due to the dropping of observations separated by a fixed effect (Correia et al., 2019).

B.3 Language

In this section, we check if the results we find are driven by language similarity. To do so, we follow the two language similarity measures from Kone et al. (2018). Define ϑ_i^l as the share of people with mother tongue l in district i. Then, the common language measure between districts i and j is

$$commlang_{ij} = \sum_l \vartheta_i^l \vartheta_j^l.$$

We can also define a language overlap measure, defined as

$$overlang_{ij} = \sum_l \min\left\{\vartheta_i^l, \vartheta_j^l\right\}.$$

In both cases, the larger the measures, the less likely it should be for people in these districts to face communication barriers. Table A6 presents the results of the intensive margin regression after considering the language measures. We find that none of the measures is statistically significant. This suggests that the cultural proximity result is not driven by firms sharing the same language.

Table A6: Effect of cultural proximity and language on trade, intensive margin

Dep. Variable	(1) Log Sales	(2) Log Transactions	(3) Log Sales	(4) Log Transactions
BC	0.108***	0.068**	0.108***	0.068**
	(0.033)	(0.028)	(0.033)	(0.028)
commlang	-0.322	-0.126		
	(0.389)	(0.305)		
overlang			-0.419	-0.061
			(0.406)	(0.324)
Obs.	30,703	30,703	30,703	30,703
Adj. R2	0.409	0.357	0.409	0.357
FE	Seller, buyer	Seller, buyer	Seller, buyer	Seller, buyer

Notes: This table shows the results of estimating a modified version of Equation 1. ***, ** and * indicate statistical significance at the 99, 95, and 90 percent levels respectively. Standard errors two-way clustered at the seller and buyer level. Standard errors are in parentheses. A higher Kullback-Leibler divergence means two firms are socially farther away.

B.4   Goods specialization

The cultural groups in India are, in many cases, defined by the production of specific goods (Munshi, 2019).[28] In this section, we study whether the cultural proximity results are cultural groups specializing in the production of certain goods and, given this, forming special bonds with their specific set of buyers.

First, we assign each firm to a unique cultural group. We do this by assigning each firm to the cultural group to which it has the highest probability of belonging to. In second place, we see which is the most important 4-digit HS code in terms of sales and purchases for each cultural group. We then match each firm to which is the good its cultural group specializes in selling and buying. Working with a version of our dataset at the transaction level, we estimate the regression

$$\ln n_g\left(\nu, \omega, t\right) = \iota_{\nu g} + \iota_{gt} + \iota_\omega + \delta BC\left(\nu, \omega\right) + \xi\left(BC\left(\nu, \omega\right) \times \mathbb{I}_g^{spec}\right) + \eta \ln dist\left(\nu, \omega\right) + \epsilon_g\left(\nu, \omega\right),$$
(A3)

where $\mathbb{I}_g^{spec}$ indicates if the good being traded is one in which either the cultural group of the selling firm specializes in selling or the cultural group of the buying firm specializes in buying. Table A7 presents the results for the sales.

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[28] We can also understand this as certain cultural groups specializing in certain occupations.

First, if the cultural proximity results were only driven by cultural groups producing specific specialized goods, then we would expect the term on cultural proximity to be close to zero, and the term on the interactions to be statistically different from zero. However, we find that cultural proximity matters for all types of goods: for those in which a cultural group specializes and for those in which a cultural group does not specialize.

Second, in Column 2, we find that the coefficient on the interaction term is positive and statistically significant. Nevertheless, we lose this statistical significance after controlling for additional variables in Column 4. This could point to cultural proximity mattering more for those goods in which cultural groups specialize in buying, but the result is not conclusive.

All in all, the results suggest that specialization does not play a role in the determination of the effect of cultural proximity on trade.

Table A7: Effect of cultural proximity on trade by good specialization, intensive margin

	(1)	(2)	(3)	(4)
Dep. Variable	Log Sales	Log Sales	Log Sales	Log Sales
BC	0.072***	0.071***	0.064***	0.064***
	(0.026)	(0.025)	(0.023)	(0.023)
$BC \times \mathbb{I}_g^{spec,seller}$	-0.016		0.135	
	(0.160)		(0.304)	
$BC \times \mathbb{I}_g^{spec,buyer}$		0.152***		0.185
		(0.008)		(0.118)
Obs.	226,039	226,039	229,719	229,719
Adj. R2	0.853	0.853	0.854	0.854
FE	Seller×HS, buyer, month×HS	Seller×HS, buyer, month×HS	Seller×HS, buyer, month×HS, origin×dest.	Seller×HS, buyer, month×HS, origin×dest.

Notes: This table shows the results of estimating Equation A3. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent levels respectively. Good g is defined according to 6-digit HS classification. Sales were trimmed by 4-digit HS code at 5 and 95 percent. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors are two-way clustered at the seller and 4-digit HS level. Standard errors are in parentheses. The higher the Bhattacharyya coefficient, the culturally closer the two firms are. The number of observations varies between specifications due to the dropping of observations separated by a fixed effect (Correia et al., 2019). $\mathbb{I}_g^{spec,seller}$ indicates the good g is the good in which the seller's cultural group specializes in selling. $\mathbb{I}_g^{spec,buyer}$ indicates the good g is the good in which the buyer's cultural group specializes in buying.

B.5 Industry pair linkages

In this section, we revise the intensive margin regressions after considering that there are pairs of industries that are bound to trade more than other pairs. For instance, perhaps certain castes happen to specialize in certain industries, and these industries are more likely to trade with each other. For this analysis, we add an industry of seller $\times$ industry of buyer fixed effect to Equation 1. The sectors are based on the 4-digit HS code of the good with the highest sales for each firm. Table A8 presents the results. When compared to the results in Table 1, we find that, while the effect of cultural proximity is slightly higher, the main message prevails.

Table A8: Effect of cultural proximity after controlling for industries, intensive margin

	(1)	(2)	(3)	(4)
Dep. Variable	Log Sales	Log Transactions	Log Sales	Log Transactions
BC	0.105**	0.089**	0.145***	0.104**
	(0.052)	(0.043)	(0.055)	(0.045)
Obs.	16,194	16,194	16,229	16,229
Adj. R2	0.414	0.326	0.395	0.308
FE	Seller, buyer, seller ind.×buyer ind.	Seller, buyer, seller ind.×buyer ind.	Seller, buyer, origin×dest., seller ind.×buyer ind.	Seller, buyer, origin×dest., seller ind.×buyer ind.

Notes: Columns 1, 2, 3 and 4 show the results of estimating Equation 1. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent levels respectively. Origin-destination fixed effect considers the district of the seller and the buyer. An industry is classified according to the 4-digit HS classification of the most sold good by each firm. Standard errors are two-way clustered at the seller and buyer level. Standard errors are in parentheses. The higher the Bhattacharyya coefficient, the culturally closer two firms are. Number of observations varies between specifications due to the dropping of observations separated by a fixed effect (Correia et al., 2019).

C Model

C.1 Preferences

A representative household demands goods from firms with CES $\sigma > 1$, the elasticity of substitution between goods, and inelastically supplies labor to firms. The household maximizes utility

$$\max_{\{y(\omega)\}} \left(\int_{\omega \in \Omega} y(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}, \ s.t. \int_{\omega \in \Omega} P(\omega) y(\omega) d\omega \leq Y,$$

where $y(\omega)$ is the household demand for good ω, $P(\omega)$ is the price the household pays for good ω, Ω is the set of goods in the economy, and Y is total income. This generates the demand for good ω

$$x(\omega) = P(\omega)^{1-\sigma} P^{\sigma-1} Y, \tag{A4}$$

where $x(\omega) \equiv P(\omega) y(\omega)$, and $P \equiv \left(\int_{\omega \in \Omega} P(\omega)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$ is a CES price index.

C.2 Technology

There is a continuum of firms that operate under monopolistic competition and produce differentiated goods indexed by ω. Since each firm produces a unique good, ω denotes a firm or a good. We consider a roundabout production economy, so firms can purchase intermediate inputs from all firms in the economy. Each firm produces its differentiated good with hired labor from the representative household and intermediate inputs.

Firms operate in three steps. First, sellers endogenously choose buyers (i.e. matching). In particular, a seller ν sells to buyer ω whenever the profits of doing so are larger than the fixed costs of matching $\epsilon F(\nu, \omega)$. Guided by our stylized facts, we argue that cultural proximity $BC(\nu, \omega)$ between seller ν and buyer ω determines the pairwise matching costs $F(\nu, \omega)$. Indeed, previous work describes how culture encodes information that is useful for sellers to decide which buyer to sell to (Allen et al., 2019; Balmaceda and Escobar, 2017).[29]

Second, upon matching, due to the risk of buyers withholding payment, sellers charge a premium to buyers (i.e. terms of trade). In particular, the price that seller ν charges to buyer ω includes a premium $d(\nu, \omega) \geq 1$, which is a function of different factors that influence the hold-up process. Guided by our stylized facts, we posit that cultural proximity

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[29]There could be other microfoundations motivating how culture influences matching costs (e.g. risk-sharing as in Ambrus et al. 2014; Bloch et al. 2008. These would generate similar frictions at the extensive and intensive margin.

$BC(\nu, \omega)$ between seller ν and buyer ω determines $d(\nu, \omega)$. This is similar to earlier work on how culture can be an informal institutional channel to solve hold-up problems.[30] Third, sellers and buyers trade.

Step 1: Matching. In the first step, we endogenize sellers selecting which buyers to trade with by laying out the maximization problem of firms, and how cultural proximity influences it. A seller ν matches with buyer ω whenever the seller's profits of doing so $\pi(\nu, \omega)$ are larger than the fixed costs of matching $\epsilon F(\nu, \omega)$, where $F(\nu, \omega)$ are pairwise fixed costs of matching, and ϵ are i.i.d. log normal errors with mean $\mu_{\ln(\epsilon)}$ and standard deviation $\sigma_{\ln(\epsilon)}$. It can be shown that profits are proportional to the value of intermediate sales $n(\nu, \omega)$ from seller ν to buyer ω, such that

$$\pi(\nu, \omega) = \frac{n(\nu, \omega)}{\sigma}. \tag{A5}$$

Sellers are looking for buyers, and vice-versa. Firms can meet costlessly, so all firms can meet each other before deciding who to match with. The purpose of a meeting is to infer the fixed costs the seller would incur if they were to trade with each buyer. Here we rationalize how sellers infer the costs of matching arising from cultural proximity. We assume that each firm owner has a name and that sellers and buyers exchange names upon meeting. Then, each name has a probability mapping to different cultural groups. We assume that this mapping is public information. So, for example, we assume that all firm owners know that the surname *Shah* is associated with either of the three groups: Jain, Muslim (Faqir), or Hindu (Vaishnav baniya), with probabilities reflecting the empirical distribution.

For each cultural group j, we consider the matching function

$$M^j(\nu, \omega) = (\rho_\nu(j))^\varphi (\rho_\omega(j))^{1-\varphi},$$

where $\rho_\nu(j)$ is the probability that seller ν belongs to cultural group j, $\rho_\omega(j)$ is the probability that buyer ω belongs to cultural group j, φ is the weight of ν to determine their proximity. For simplicity, we assume $\varphi = \frac{1}{2}$. The expected proximity between ν and ω is

$$\overline{M}(\nu, \omega) = \frac{1}{\mathcal{X}} \sum_{j=1}^{\mathcal{X}} M^j(\nu, \omega) \propto BC(\nu, \omega).$$

That is, the expected proximity between seller ν and buyer ω is proportional to the Bhattacharyya coefficient we use in the empirical part of the paper to measure cultural proximity

---

[30]Again, this would be consistent with other microfoundations on how culture influences trade costs due to reputation (Banerjee and Duflo, 2000; Chen and Wu, 2021) or loyalty (Board, 2011).

between firms. Finally, following our stylized facts, the fixed costs of matching are a function of cultural proximity such that $F(\nu, \omega) = f\left(\overline{M}(\nu, \omega)\right)$, where $f(\cdot)$ is an exponential function for simplicity. Our modeling decision allows for the fact that a firm belonging to a cultural group encodes information that other firms use to determine the cost of matching. Then, we consider

$$F(\nu, \omega) = \kappa + \exp\left(-\gamma BC(\nu, \omega)\right), \tag{A6}$$

where $\gamma > 0$ measures the sensitivity of the pairwise matching cost to the cultural proximity $BC(\nu, \omega)$, and κ is a scaling constant.

The intuition behind parameter γ is that it encases court quality, such that $\gamma = \gamma\left(\mathbb{I}^{court}\right)$, where $\mathbb{I}^{court}$ is an indicator of low court quality. In this sense, Table A1 in Appendix A suggests that parameter γ increases in magnitude when $\mathbb{I}^{court} = 1$ and firms face weak court quality. The lower the quality of courts is, the larger parameter γ is, and the more firms rely on cultural proximity to match.

We now describe how firms match. Before the formation of the network, firms are characterized by $\lambda = (z, \boldsymbol{\rho})$, where z is productivity, and $\boldsymbol{\rho}$ is the vector of probabilities of firm λ belonging to each cultural group. After firms meet each other and infer their cultural proximity, firms now only differ in their productivity z. So the share of seller-buyer pairs (z, z') is

$$l\left(z, z'\right) = \int \mathbb{I}\left[\ln\left(\pi\left(z, z'\right)\right) - \ln\left(F\left(z, z'\right)\right) - \ln\left(\epsilon\left(z, z'\right)\right) > 0\right] dH\left(\epsilon\left(z, z'\right)\right), \tag{A7}$$

where $l\left(z, z'\right)$ is called the *link function*. From Equations 7 and A7, we see that the higher the cultural proximity, the lower the matching cost and the larger the probability of matching. This relates to Stylized Fact 2.

Step 2: Terms of the contract. After matching, seller ν and buyer ω set up the terms of the contract. We first consider the possibility that the buyer may withhold payment after the seller ships the goods. The seller's concerns around this issue can be monetized in the premium that the seller charges to the buyer. This premium gets passed to the unit price $p(\nu, \omega)$ that results from profit maximization

$$p(\nu, \omega) = \mu c(\nu) d(\nu, \omega), \tag{A8}$$

where $c(\nu)$ is the marginal cost and $\mu \equiv \frac{\sigma}{\sigma-1}$ is a markup.

We now turn to explain the premium $d(\nu, \omega)$. Time is continuous within our one-period

static model. Seller ν considers the time T that buyer ω withholds payment for the first time is a random variable. T follows an exponential distribution with intensity rate $\delta(\nu, \omega)$. Then, the probability seller ν waits for more than t units of time until buyer ω withholds payment for the first time is

$$
\begin{aligned}
P(T > t) &= 1 - P(T \leq t), \\
&= 1 - (1 - \exp(-\delta(\nu, \omega) t)), \\
&= \exp(-\delta(\nu, \omega) t).
\end{aligned}
$$

Seller ν cares that buyer ω never withholds payment. Then, the probability $\bar{p}$ that seller ν waits more than a unit of time until buyer ω withholds payment is

$$
\begin{aligned}
\bar{p} &= P(T > 1), \\
&= \exp(-\delta(\nu, \omega)).
\end{aligned}
$$

Then, the expected number of times buyer ω withholds payment is $\frac{1}{\bar{p}}$. We posit that the premium $d(\nu, \omega)$ is proportional to the expected number of times buyer ω withholds payment to seller ν. The intuition is that seller ν will charge a higher premium if there is a higher hold-up risk from buyer ω. For simplicity,

$$
\begin{aligned}
d(\nu, \omega) &= \frac{1}{\bar{p}} \geq 1, \\
&= \exp(\delta(\nu, \omega)).
\end{aligned}
$$

Finally, we allow $\delta(\nu, \omega)$ to include a set of covariates that affects the terms of trade. For example, inputs can spoil or get lost more easily with larger distances, which increases the probability of buyer ω not paying seller ν since the goods did not arrive as agreed.

More importantly, guided by our stylized facts, we allow for the fact that, upon matching, cultural proximity $BC(\nu, \omega)$ also influences $\delta(\nu, \omega)$. In particular, we consider

$$
d(\nu, \omega) = \exp(\beta BC(\nu, \omega) + \epsilon(\nu, \omega)), \tag{A9}
$$

where $\beta < 0$ is a trade cost semi-elasticity, and $\epsilon(\nu, \omega)$ are unobservables.

From Equation A8, we have that the higher the cultural proximity, the lower the prices, which relates to Stylized Fact 3. Likewise, from Equation 9, we see that the higher the cultural proximity, the higher the intermediate sales, which relates to Stylized Fact 1.

The economic intuition of parameter β is that it incorporates information on court quality, such that $\beta = \beta\left(\mathbb{I}^{court}\right)$. Based on the result of Table 4, we know model parameter β increases in magnitude when $\mathbb{I}^{court} = 1$ and firms face bad courts. Therefore, parameter β relates to how firms respond to court quality: the lower the quality of the courts, the larger the magnitude of parameter β, and the more important cultural proximity is for trade.

Step 3: Trade. Finally, we model trade. Each firm has a technology

$$y\left(\omega\right) = \kappa_{\alpha} z\left(\omega\right) l\left(\omega\right)^{\alpha} m\left(\omega\right)^{1-\alpha}, \tag{A10}$$

where $y\left(\omega\right)$ is output, $\kappa_{\alpha} \equiv \frac{1}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}$ is a normalization constant, $z\left(\omega\right)$ is firm-level productivity, $l\left(\omega\right)$ is labor, and $m\left(\omega\right)$ are intermediate inputs from other firms. In turn, the intermediate inputs are defined as a CES composite so

$$m\left(\omega\right) = \left(\int_{\nu \in \Omega(\omega)} m\left(\nu,\omega\right)^{\frac{\sigma-1}{\sigma}} d\nu\right)^{\frac{\sigma}{\sigma-1}},$$

where $m\left(\nu,\omega\right)$ is quantity of inputs from seller ν to buyer ω, $\sigma > 1$ is the elasticity of substitution across intermediates, and $\Omega\left(\omega\right)$ is the endogenous set of suppliers of buyer ω. By cost minimization, we get

$$c\left(\omega\right) = \frac{P\left(\omega\right)^{1-\alpha}}{z\left(\omega\right)}, \tag{A11}$$

where $P\left(\omega\right) \equiv \left(\int_{\nu \in \Omega(\omega)} p\left(\nu,\omega\right)^{1-\sigma} d\nu\right)^{\frac{1}{1-\sigma}}$ is a CES price index across prices of intermediates, and labor is the numeraire good, so $w = 1$. Profit maximization subject to demand generates constant markup pricing such that the unit price is $p\left(\nu,\omega\right) = \mu c\left(\nu\right) d\left(\nu,\omega\right)$, as stated before.

We now derive the demand for intermediates, so

$$n\left(\nu,\omega\right) = p\left(\nu,\omega\right)^{1-\sigma} P\left(\omega\right)^{\sigma-1} N\left(\omega\right), \tag{A12}$$

where $N\left(\omega\right) = \int_{\nu \in \Omega(\omega)} n\left(\nu,\omega\right) d\nu$ is the total intermediate purchases by buyer ω and $n\left(\nu,\omega\right) \equiv p\left(\nu,\omega\right) m\left(\nu,\omega\right)$ is the value of purchases from seller ν to buyer ω. From Equation A12 we can obtain the gravity equation as

$$\log\left(n\left(\nu,\omega\right)\right) = \iota_{\nu} + \iota_{\omega} + \left(1-\sigma\right) \log\left(d\left(\nu,\omega\right)\right), \tag{A13}$$

where ι_{ν} and ι_{ω} are seller and buyer fixed effects. Here, the premium $d\left(\nu,\omega\right)$ enters the

gravity equation as a trade cost. This gravity equation relates directly to Equation 1 that we estimate.

C.3 Equilibrium given extensive margin

Conditional on the extensive margin (i.e. sellers matching with buyers), firms only differ in productivity z. Based on the price index of all of the goods acquired by firm z', we get

$$P\left(z'\right)^{1-\sigma} = \mu^{1-\sigma} \int P(z)^{(1-\alpha)(1-\sigma)} z^{\sigma-1} d\left(z, z'\right)^{1-\sigma} l\left(z, z'\right) dG(z), \qquad \text{(A14)}$$

where $l\left(z, z'\right)$ is the share of sellers of productivity z that sell to buyers with productivity z', also called the *link function*. Now, total sales of firm z is the sum of sales to households plus intermediates, so

$$S(z) = \begin{aligned}&\left[\mu^{1-\sigma} P(z)^{(1-\alpha)(1-\sigma)} z^{\sigma-1}\right] \times \\ &\left[\frac{Y}{P^{1-\sigma}} D(z)^{1-\sigma} + \left(\frac{1-\alpha}{\mu}\right)\left(\int\left[d\left(z, z'\right)^{1-\sigma} P\left(z'\right)^{\sigma-1} S\left(z'\right)\right] l\left(z, z'\right) dG\left(z'\right)\right)\right],\end{aligned}$$
$$\text{(A15)}$$

where $D(z) = \int_{\omega \in \Omega(\nu)} d(\nu, \omega) d\omega = \int d\left(z, z'\right) l\left(z, z'\right) dG\left(z'\right)$ is the aggregated wedge for firm of productivity z.

D Model derivations

In this section, we include details about the derivations of the theoretical model.

D.1 Technology

A unique variety ω is produced by a single firm which minimizes its unit cost of production subject to its production technology, so

$$\min_{\{m(\nu,\omega)\}} \int_{\nu \in \Omega(\omega)} m(\nu, \omega) p(\nu, \omega) d\nu + wl(\omega), s.t.$$

$$y(\omega) = \kappa_\alpha z(\omega) l(\omega)^\alpha m(\omega)^{1-\alpha},$$

$$m(\omega) = \left(\int_{\nu \in \Omega(\omega)} m(\nu, \omega)^{\frac{\sigma-1}{\sigma}} d\nu\right)^{\frac{\sigma}{\sigma-1}},$$

$$y(\omega) = 1.$$

Merge the first and third constraints, such that

$$y(\omega) = \kappa_\alpha z(\omega) l(\omega)^\alpha m(\omega)^{1-\alpha},$$

$$1 = \kappa_\alpha z(\omega) l(\omega)^\alpha m(\omega)^{1-\alpha},$$

$$l(\omega)^\alpha = \frac{1}{\kappa_\alpha z(\omega) m(\omega)^{1-\alpha}},$$

$$= \kappa_\alpha^{-1} z(\omega)^{-1} m(\omega)^{\alpha-1},$$

$$l(\omega) = \kappa_\alpha^{-\frac{1}{\alpha}} z(\omega)^{-\frac{1}{\alpha}} m(\omega)^{\frac{\alpha-1}{\alpha}}.$$

Rewrite the minimization problem, such that

$$\min_{\{m(\nu,\omega)\}} \int_{\nu\in\Omega(\omega)} m(\nu,\omega) p(\nu,\omega) d\nu + wl(\omega),$$

$$\int_{\nu\in\Omega(\omega)} m(\nu,\omega) p(\nu,\omega) d\nu + \kappa_\alpha^{-\frac{1}{\alpha}} wz(\omega)^{-\frac{1}{\alpha}} m(\omega)^{\frac{\alpha-1}{\alpha}},$$

$$\int_{\nu\in\Omega(\omega)} m(\nu,\omega) p(\nu,\omega) d\nu + \kappa_\alpha^{-\frac{1}{\alpha}} wz(\omega)^{-\frac{1}{\alpha}} \left(\int_{\nu\in\Omega(\omega)} m(\nu,\omega)^{\frac{\sigma-1}{\sigma}} d\nu \right)^{\frac{\sigma}{\sigma-1}\frac{\alpha-1}{\alpha}}.$$

The first order condition with respect to $m(\nu,\omega)$ is

$$0 = p(\nu,\omega) + \kappa_\alpha^{-\frac{1}{\alpha}} wz(\omega)^{-\frac{1}{\alpha}} \left(\frac{\sigma}{\sigma-1}\frac{\alpha-1}{\alpha}\right) (\dots)^{\frac{\sigma}{\sigma-1}\frac{\alpha-1}{\alpha}-1} \left(\frac{\sigma-1}{\sigma}\right) m(\nu,\omega)^{\frac{\sigma-1}{\sigma}-1},$$

$$p(\nu,\omega) = \kappa_\alpha^{-\frac{1}{\alpha}} \left(\frac{1-\alpha}{\alpha}\right) wz(\omega)^{-\frac{1}{\alpha}} (\dots)^{\frac{\sigma}{\sigma-1}\frac{\alpha-1}{\alpha}-1} m(\nu,\omega)^{-\frac{1}{\sigma}},$$

$$m(\nu,\omega)^{\frac{1}{\sigma}} = \frac{\kappa_\alpha^{-\frac{1}{\alpha}} \left(\frac{1-\alpha}{\alpha}\right) wz(\omega)^{-\frac{1}{\alpha}} (\dots)^{\frac{\sigma}{\sigma-1}\frac{\alpha-1}{\alpha}-1}}{p(\nu,\omega)},$$

$$m(\nu,\omega) = \frac{\kappa_\alpha^{-\frac{\sigma}{\alpha}} \left(\frac{1-\alpha}{\alpha}\right)^\sigma w^\sigma z(\omega)^{-\frac{\sigma}{\alpha}} (\dots)^{\sigma\left(\frac{\sigma}{\sigma-1}\frac{\alpha-1}{\alpha}-1\right)}}{p(\nu,\omega)^\sigma}.$$

Now, the first order condition with respect to $m(\nu,\omega)$ is

$$m(\nu,\omega) = \frac{\kappa_\alpha^{-\frac{\sigma}{\alpha}} \left(\frac{1-\alpha}{\alpha}\right)^\sigma w^\sigma z(\omega)^{-\frac{\sigma}{\alpha}} (\dots)^{\sigma\left(\frac{\sigma}{\sigma-1}\frac{\alpha-1}{\alpha}-1\right)}}{p(\nu',\omega)^\sigma}.$$

We divide both first order conditions, such that

$$
\frac{m\left(\nu,\omega\right)}{m\left(\nu',\omega\right)} = \frac{\frac{\kappa_\alpha^{-\frac{\sigma}{\alpha}}\left(\frac{1-\alpha}{\alpha}\right)^\sigma w^\sigma z(\omega)^{-\frac{\sigma}{\alpha}}(...)^{\sigma\left(\frac{\sigma}{\sigma-1}\frac{\alpha-1}{\alpha}-1\right)}}{p(\nu,\omega)^\sigma}}{\frac{\kappa_\alpha^{-\frac{\sigma}{\alpha}}\left(\frac{1-\alpha}{\alpha}\right)^\sigma w^\sigma z(\omega)^{-\frac{\sigma}{\alpha}}(...)^{\sigma\left(\frac{\sigma}{\sigma-1}\frac{\alpha-1}{\alpha}-1\right)}}{p(\nu',\omega)^\sigma}},
$$

$$
= \frac{\frac{z(\omega)^{-\frac{\sigma}{\alpha}}}{p(\nu,\omega)^\sigma}}{\frac{z(\omega)^{-\frac{\sigma}{\alpha}}}{p(\nu',\omega)^\sigma}},
$$

$$
= \frac{p\left(\nu',\omega\right)^\sigma}{p\left(\nu,\omega\right)^\sigma},
$$

$$
m\left(\nu',\omega\right) = \frac{p\left(\nu,\omega\right)^\sigma m\left(\nu,\omega\right)}{p\left(\nu',\omega\right)^\sigma}.
$$

We plug this expression back into the expression for the composite of intermediates, so

$$
m\left(\omega\right) = \left(\int_{\nu'\in\Omega(\omega)} m\left(\nu',\omega\right)^{\frac{\sigma-1}{\sigma}} d\nu\right)^{\frac{\sigma}{\sigma-1}},
$$

$$
= \left(\int_{\nu'\in\Omega(\omega)} \left(\frac{p\left(\nu,\omega\right)^\sigma m\left(\nu,\omega\right)}{p\left(\nu',\omega\right)^\sigma}\right)^{\frac{\sigma-1}{\sigma}} d\nu\right)^{\frac{\sigma}{\sigma-1}},
$$

$$
= p\left(\nu,\omega\right)^\sigma m\left(\nu,\omega\right) \underbrace{\left(\int_{\nu'\in\Omega(\omega)} p\left(\nu',\omega\right)^{1-\sigma} d\nu\right)^{\frac{\sigma}{\sigma-1}}}_{=\left(P(\omega)^{1-\sigma}\right)^{\frac{\sigma}{\sigma-1}}},
$$

$$
= p\left(\nu,\omega\right)^\sigma m\left(\nu,\omega\right)\left(P\left(\omega\right)^{1-\sigma}\right)^{\frac{\sigma}{\sigma-1}},
$$

$$
= p\left(\nu,\omega\right)^\sigma m\left(\nu,\omega\right) P\left(\omega\right)^{-\sigma},
$$

$$
= m\left(\omega\right) p\left(\nu,\omega\right)^{-\sigma} P\left(\omega\right)^\sigma,
$$

$$
p\left(\nu,\omega\right) m\left(\nu,\omega\right) = m\left(\omega\right) p\left(\nu,\omega\right)^{1-\sigma} P\left(\omega\right)^\sigma,
$$

$$
n\left(\nu,\omega\right) = P\left(\omega\right) m\left(\omega\right) p\left(\nu,\omega\right)^{1-\sigma} P\left(\omega\right)^{\sigma-1},
$$

$$
= N\left(\omega\right) p\left(\nu,\omega\right)^{1-\sigma} P\left(\omega\right)^{\sigma-1},
$$

which is the demand of firm ω from variety ν, where $P\left(\omega\right)^{1-\sigma} = \int_{\nu\in\Omega(\omega)} p\left(\nu,\omega\right)^{1-\sigma} d\nu$ is the price index faced by firm ω, $n\left(\nu,\omega\right) = p\left(\nu,\omega\right) m\left(\nu,\omega\right)$ is the expenditure of ω on variety ν, and $N\left(\omega\right) = P\left(\omega\right) m\left(\omega\right)$ is the total expenditure of firm ω.

The expression for the unit cost of production is

$$c\left(\omega\right) = \frac{w^{\alpha} P\left(\omega\right)^{1-\alpha}}{z\left(\omega\right)},$$

$$= \frac{P\left(\omega\right)^{1-\alpha}}{z\left(\omega\right)},$$

where wages $w = 1$ is the numeraire price.

Now, firms engage in monopolistic competition since they produce a unique variety. In particular, firm ν maximizes profits by selling its good to buyers ω subject to the demand for its intermediate, so

$$\max_{\{p(\nu,\omega)\}} \int_{\omega \in \Omega(\nu)} \left(p\left(\nu,\omega\right) - d\left(\nu,\omega\right) c\left(\nu\right)\right) m\left(\nu,\omega\right), s.t.$$

$$m\left(\nu,\omega\right) = m\left(\omega\right) p\left(\nu,\omega\right)^{-\sigma} P\left(\omega\right)^{\sigma},$$

where $d\left(\nu,\omega\right)$ is the iceberg cost of firm ν selling to ω. Rewrite the profit function $\pi\left(\nu,\omega\right)$, such that

$$\pi\left(\nu,\omega\right) = \left(p\left(\nu,\omega\right) - d\left(\nu,\omega\right) c\left(\nu\right)\right) m\left(\nu,\omega\right),$$

$$= p\left(\nu,\omega\right) m\left(\nu,\omega\right) - d\left(\nu,\omega\right) c\left(\nu\right) m\left(\nu,\omega\right),$$

$$= p\left(\nu,\omega\right) m\left(\omega\right) p\left(\nu,\omega\right)^{-\sigma} P\left(\omega\right)^{\sigma} - d\left(\nu,\omega\right) c\left(\nu\right) m\left(\omega\right) p\left(\nu,\omega\right)^{-\sigma} P\left(\omega\right)^{\sigma},$$

$$= m\left(\omega\right) p\left(\nu,\omega\right)^{1-\sigma} P\left(\omega\right)^{\sigma} - d\left(\nu,\omega\right) c\left(\nu\right) m\left(\omega\right) p\left(\nu,\omega\right)^{-\sigma} P\left(\omega\right)^{\sigma}.$$

The first order condition is

$$[p\left(\nu,\omega\right)] : \left(1 - \sigma\right) m\left(\omega\right) p\left(\nu,\omega\right)^{-\sigma} P\left(\omega\right)^{\sigma}$$

$$- \left(-\sigma\right) d\left(\nu,\omega\right) c\left(\nu\right) m\left(\omega\right) p\left(\nu,\omega\right)^{-\sigma-1} P\left(\omega\right)^{\sigma} = 0,$$

$$\left(\sigma - 1\right) m\left(\omega\right) p\left(\nu,\omega\right)^{-\sigma} P\left(\omega\right)^{\sigma} = \sigma d\left(\nu,\omega\right) c\left(\nu\right) m\left(\omega\right) p\left(\nu,\omega\right)^{-\sigma-1} P\left(\omega\right)^{\sigma},$$

$$\left(\sigma - 1\right) = \sigma d\left(\nu,\omega\right) c\left(\nu\right) p\left(\nu,\omega\right)^{-1},$$

$$p\left(\nu,\omega\right) = \left(\frac{\sigma}{\sigma - 1}\right) c\left(\nu\right) d\left(\nu,\omega\right),$$

$$= \mu c\left(\nu\right) d\left(\nu,\omega\right),$$

where $\mu = \frac{\sigma}{\sigma-1}$ is the markup.

D.2 Preferences

A representative household maximizes its utility subject to its budget constraint, so

$$\max_{\{y(\omega)\}} \left(\int_{\omega \in \Omega} y(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}, \quad s.t. \int_{\omega \in \Omega} P(\omega) y(\omega) d\omega \leq Y,$$

The first order condition with respect to firm ω is

$$[y(\omega)] : \left(\frac{\sigma}{\sigma-1} \right) (\ldots)^{\frac{\sigma}{\sigma-1}-1} \left(\frac{\sigma-1}{\sigma} \right) y(\omega)^{\frac{\sigma-1}{\sigma}-1} = \lambda P(\omega),$$

$$\lambda P(\omega) = (\ldots)^{\frac{\sigma}{\sigma-1}-1} y(\omega)^{-\frac{1}{\sigma}},$$

where λ is the Lagrangian multiplier of the budget constraint, and $(\ldots)$ is an aggregate term we do not write down since it will cancel out during the derivation. Now, the first order condition with respect to another firm ω' is

$$\lambda P(\omega') = (\ldots)^{\frac{\sigma}{\sigma-1}-1} y(\omega')^{-\frac{1}{\sigma}}.$$

We then divide both first-order conditions, such that

$$\frac{\lambda P(\omega)}{\lambda P(\omega')} = \frac{(\ldots)^{\frac{\sigma}{\sigma-1}-1} y(\omega)^{-\frac{1}{\sigma}}}{(\ldots)^{\frac{\sigma}{\sigma-1}-1} y(\omega')^{-\frac{1}{\sigma}}},$$

$$\frac{P(\omega)}{P(\omega')} = \frac{y(\omega)^{-\frac{1}{\sigma}}}{y(\omega')^{-\frac{1}{\sigma}}},$$

$$= \frac{y(\omega')^{\frac{1}{\sigma}}}{y(\omega)^{\frac{1}{\sigma}}},$$

$$y(\omega')^{\frac{1}{\sigma}} = y(\omega)^{\frac{1}{\sigma}} \frac{P(\omega)}{P(\omega')},$$

$$y(\omega') = y(\omega) \left(\frac{P(\omega)}{P(\omega')} \right)^{\sigma}.$$

We plug this demand back into the budget constraint, which holds with equality, so

$$Y = \int_{\omega' \in \Omega} P(\omega') y(\omega') d\omega,$$

$$= \int_{\omega' \in \Omega} P(\omega') \left[y(\omega) \left(\frac{P(\omega)}{P(\omega')} \right)^{\sigma} \right] d\omega,$$

$$= y(\omega) P(\omega)^{\sigma} \underbrace{\int_{\omega' \in \Omega} P(\omega')^{1-\sigma} d\omega}_{=P^{1-\sigma}},$$

$$= y(\omega) P(\omega)^{\sigma} P^{1-\sigma},$$

$$= (P(\omega) y(\omega)) P(\omega)^{\sigma-1} P^{1-\sigma},$$

$$= x(\omega) P(\omega)^{\sigma-1} P^{1-\sigma},$$

$$x(\omega) = P(\omega)^{1-\sigma} P^{\sigma-1} Y,$$

which is the demand function for the unique variety of firm ω, where $P^{1-\sigma} = \int_{\omega \in \Omega} P(\omega)^{1-\sigma} d\omega$ is the CES aggregate price index, and $x(\omega) = P(\omega) y(\omega)$ is the expenditure on a variety ω.

D.3 Gravity of intermediates

By plugging the pricing equation in the demand of firm ω for intermediates from firm ν, we derive the firm-level gravity equation

$$
\begin{aligned}
n\left(\nu,\omega\right) &= p\left(\nu,\omega\right)^{1-\sigma} P\left(\omega\right)^{\sigma-1} N\left(\omega\right), \\
&= \left(\mu c\left(\nu\right) d\left(\nu,\omega\right)\right)^{1-\sigma} P\left(\omega\right)^{\sigma-1} N\left(\omega\right), \\
&= \mu^{1-\sigma} d\left(\nu,\omega\right)^{1-\sigma} c\left(\nu\right)^{1-\sigma} P\left(\omega\right)^{\sigma-1} N\left(\omega\right), \\
\log\left(n\left(\nu,\omega\right)\right) &= \log\left(\mu^{1-\sigma} d\left(\nu,\omega\right)^{1-\sigma} c\left(\nu\right)^{1-\sigma} P\left(\omega\right)^{\sigma-1} N\left(\omega\right)\right), \\
&= \log\left(\mu^{1-\sigma}\right) + \log\left(c\left(\nu\right)^{1-\sigma}\right) + \log\left(P\left(\omega\right)^{\sigma-1} N\left(\omega\right)\right) + \log\left(d\left(\nu,\omega\right)^{1-\sigma}\right), \\
&= \iota + \iota_\nu + \iota_\omega + \left(1-\sigma\right)\log\left(d\left(\nu,\omega\right)\right),
\end{aligned}
$$

where ι is an intercept, ι_ν are seller fixed effects, and ι_ω are buyer fixed effects.

D.4 Equilibrium given the extensive margin

In this section, we derive the expression for the equilibrium objects given the structure of the production network. We first derive the recursive expression for prices, and then for total sales.

Recursive expression for prices. Consider the expression for the CES price index, so

$$P(\omega)^{1-\sigma} = \int_{\nu \in \Omega(\omega)} p(\nu, \omega)^{1-\sigma} d\nu,$$

$$P(z')^{1-\sigma} = \int p(z, z')^{1-\sigma} l(z, z') dG(z),$$

$$= \int \left(\left(\frac{\sigma}{\sigma - 1} \right) c(z) d(z, z') \right)^{1-\sigma} l(z, z') dG(z),$$

$$= \mu^{1-\sigma} \int (c(z) d(z, z'))^{1-\sigma} dG(z),$$

$$= \mu^{1-\sigma} \int \left(\frac{P(z)^{1-\alpha}}{z} d(z, z') \right)^{1-\sigma} l(z, z') dG(z),$$

$$= \mu^{1-\sigma} \int \left(\frac{P(z)^{1-\alpha}}{z} d(z, z') \right)^{1-\sigma} l(z, z') dG(z),$$

$$= \mu^{1-\sigma} \int P(z)^{(1-\alpha)(1-\sigma)} z^{\sigma-1} d(z, z')^{1-\sigma} l(z, z') dG(z).$$

That is, the price index for firms of productivity z' can be expressed as a function of all other price indexes of firms z. This forms a system of equations we can solve.

Total sales. Consider the expression for total sales (i.e. sales to the household and firms), so

$$S\left(\nu\right) = x\left(\nu\right) + \int_{\omega \in \Omega(\nu)} n\left(\nu, \omega\right) d\omega,$$

$$S\left(z\right) = x\left(z\right) + \int n\left(z, z'\right) l\left(z, z'\right) dG\left(z'\right),$$

$$= P\left(z\right)^{1-\sigma} P^{\sigma-1} Y$$

$$+ \int \left[\left(\frac{\sigma}{\sigma - 1}\right)^{1-\sigma} d\left(z, z'\right)^{1-\sigma} c\left(z\right)^{1-\sigma} P\left(z'\right)^{\sigma-1} N\left(z'\right) \right] l\left(z, z'\right) dG\left(z'\right),$$

$$= P\left(z\right)^{1-\sigma} P^{\sigma-1} Y$$

$$+ \int \left[\left(\frac{\sigma}{\sigma - 1}\right)^{1-\sigma} d\left(z, z'\right)^{1-\sigma} \left[\frac{P\left(z\right)^{1-\alpha}}{z}\right]^{1-\sigma} P\left(z'\right)^{\sigma-1} N\left(z'\right) \right] l\left(z, z'\right) dG\left(z'\right),$$

$$= P\left(z\right)^{1-\sigma} P^{\sigma-1} Y$$

$$+ \left[\left(\frac{\sigma}{\sigma - 1}\right)^{1-\sigma} \left(\frac{P\left(z\right)^{1-\alpha}}{z}\right)^{1-\sigma} \right] \int \left[d\left(z, z'\right)^{1-\sigma} P\left(z'\right)^{\sigma-1} N\left(z'\right) \right] l\left(z, z'\right) dG\left(z'\right),$$

$$= \frac{P\left(z\right)^{1-\sigma} Y}{P^{1-\sigma}}$$

$$+ \left[\mu^{1-\sigma} P\left(z\right)^{(1-\alpha)(1-\sigma)} z^{\sigma-1} \right] \int \left[d\left(z, z'\right)^{1-\sigma} P\left(z'\right)^{\sigma-1} N\left(z'\right) \right] l\left(z, z'\right) dG\left(z'\right),$$

$$= \frac{\left[\left(\frac{\sigma}{\sigma-1}\right) c\left(z\right) D\left(z\right) \right]^{1-\sigma} Y}{P^{1-\sigma}}$$

$$+ \left[\mu^{1-\sigma} P\left(z\right)^{(1-\alpha)(1-\sigma)} z^{\sigma-1} \right] \int \left[d\left(z, z'\right)^{1-\sigma} P\left(z'\right)^{\sigma-1} \left(\frac{(1-\alpha) S\left(z'\right)}{\mu}\right) \right] l\left(z, z'\right) dG\left(z'\right),$$

$$= \left(\mu^{1-\sigma} P\left(z\right)^{(1-\alpha)(1-\sigma)} z^{\sigma-1} D\left(z\right)^{1-\sigma} \right) \frac{Y}{P^{1-\sigma}}$$

$$+ \left[\mu^{1-\sigma} P\left(z\right)^{(1-\alpha)(1-\sigma)} z^{\sigma-1} \right] \left[\frac{1-\alpha}{\mu}\right] \int \left[d\left(z, z'\right)^{1-\sigma} P\left(z'\right)^{\sigma-1} S\left(z'\right) \right] l\left(z, z'\right) dG\left(z'\right),$$

$$= \left[\mu^{1-\sigma} P\left(\nu\right)^{(1-\alpha)(1-\sigma)} z^{\sigma-1} \right]$$

$$\left[\frac{Y}{P^{1-\sigma}} D\left(z\right)^{1-\sigma} + \left(\frac{1-\alpha}{\mu}\right) \left(\int \left[d\left(z, z'\right)^{1-\sigma} P\left(z'\right)^{\sigma-1} S\left(z'\right) \right] l\left(z, z'\right) dG\left(z'\right) \right) \right],$$

where we use the fact that $N\left(z'\right) = \frac{(1-\alpha) S(z')}{\mu}$. Given prices $P\left(z\right)$, this forms a system of equations for sales we can solve.

E   Targeted and untargeted moments

Since the link function noise distribution affects how firms match between them, to identify the parameters related to this distribution we must target moments that are related to the extensive margin.

First, we target the mean of the log-normalized number of buyers $\ln\left(\frac{\mathcal{N}_b(\nu)}{\mathcal{N}}\right)$, where $\mathcal{N}_b(\nu)$ is the number of buyers a seller ν has; and the mean of the log-normalized number of sellers $\ln\left(\frac{\mathcal{N}_s(\omega)}{\mathcal{N}}\right)$, where $\mathcal{N}_s(\omega)$ is the number of sellers a buyer ω has. Because these two moments are related to magnitude of the matching, they should inform us about the mean of the link function noise distribution $\mu_{\ln(\epsilon)}$ and the scaling constant for the pairwise matching cost κ.

Second, this being mostly a seller-oriented model, to identify the standard deviation of the link function noise distribution $\sigma_{\ln(\epsilon)}$ we target the variance of the log-normalized number of buyers $\ln\left(\frac{\mathcal{N}_b(\nu)}{\mathcal{N}}\right)$. Lastly, to identify the standard deviation of the log-productivity distribution, we must choose a moment that is related to the variance of the intensive margin. Thus, we target the variance of the log-normalized intermediate sales $\ln\left(\frac{\widetilde{N}(\nu)}{\mathcal{N}_b(\nu)}\right)$, where $\widetilde{N}(\nu)$ is the total intermediate sales a seller ν makes.

The first untargeted moment we consider is the variance of the log-normalized number of sellers $\ln\left(\frac{\mathcal{N}_s(\omega)}{\mathcal{N}}\right)$. The second untargeted moment we examine is the variance of the log-normalized intermediate purchases $\ln\left(\frac{N(\omega)}{\mathcal{N}_s(\omega)}\right)$.

The exact definition of the targeted and untargeted moments, as well as the construction of their empirical counterparts are as follows:

Normalized number of buyers and sellers

Data. In our dataset, for each firm i, we calculate the number of firms it sold to and the number of firms it bought from. Then, to normalize this measure, we divide this number by the total number of firms in our sample. Thus, for a specific firm i, we can understand this measure as the share of firms this specific firm i is connected to, both as a buyer and a seller.

Model. For this part, we start with the link function matrix, where each element $l\left(z, z^{'}\right)$ represents the pairwise probability that seller z will match with buyer $z^{'}$. For each seller z, we take the average $l\left(z, z^{'}\right)$ across all the possible buyers. This represents the proportion of firms that seller z will match to the total number of firms. We multiply this number by the total number of firms $\mathcal{N}$ to obtain the number of buyers for each seller z. We follow a similar procedure to calculate the number of sellers each buyer $z^{'}$ has.

Normalized intermediate sales and purchases

Data. In our dataset, for each firm i, we calculate the total sales to other firms and the total purchases from other firms. In the case of the sellers, we normalize this measure by dividing the total sales of firm i by the total number of buyers this firm has. We follow a similar procedure with the buyers to calculate the normalized intermediate purchases.

Model. We use the intermediate sales matrix, where each element $n\left(z, z^{'}\right)$ represents the total sales of intermediate goods from seller z to buyer $z^{'}$. We sum all the sales for each seller z and divide this number by the number of buyers it has. Thus, we obtain the normalized intermediate sales for a given seller. For the normalized intermediate purchases, we follow a similar procedure with the buyers.

Goodness of fit. After our matching procedure, we find the parameters $\sigma_{\ln(z)} = 0.88$, $\mu_{\ln(\epsilon)} = 64.30$, $\sigma_{\ln(\epsilon)} = 10.85$ and $\kappa = 14.80$. Table A9 in Appendix E shows how the model-based moments fare against their empirical counterparts. When it comes to the targeted moments, the model can very closely replicate the empirical ones. For the untargeted moments, the model gets reasonably close to the data.

Table A9: Targeted and untargeted moments

Targeted Moments		
	Data	Model
$mean\left[\ln\left(\mathcal{N}_b\left(\nu\right)/\mathcal{N}\right)\right]$	-9.24	-9.48
$var\left[\ln\left(\mathcal{N}_b\left(\nu\right)/\mathcal{N}\right)\right]$	0.98	0.89
$var\left[\ln\left(\widetilde{N}\left(\nu\right)/\mathcal{N}_b\left(\nu\right)\right)\right]$	2.82	2.82
$mean\left[\ln\left(\mathcal{N}_s\left(\omega\right)/\mathcal{N}\right)\right]$	-9.39	-9.14
Untargeted Moments		
	Data	Model
$var\left[\ln\left(\mathcal{N}_s\left(\omega\right)/\mathcal{N}\right)\right]$	0.60	0.16
$var\left[\ln\left(N\left(\omega\right)/\mathcal{N}_s\left(\omega\right)\right)\right]$	2.73	0.56

Notes: The targeted moments are the mean of the log-normalized number of buyers $mean\left[\ln\left(\mathcal{N}_b\left(\nu\right)/\mathcal{N}\right)\right]$, the variance of the log-normalized number of buyers $var\left[\ln\left(\mathcal{N}_b\left(\nu\right)/\mathcal{N}\right)\right]$ and the variance of the log-normalized intermediate sales $var\left[\ln\left(\widetilde{N}\left(\nu\right)/\mathcal{N}_b\left(\nu\right)\right)\right]$, where $\widetilde{N}\left(\nu\right)$ are the total intermediate sales of seller ν. The untargeted moments are the mean of the log-normalized number of sellers $mean\left[\ln\left(\mathcal{N}_s\left(\omega\right)/\mathcal{N}\right)\right]$, the variance of the log-normalized number of sellers $var\left[\ln\left(\mathcal{N}_s\left(\omega\right)/\mathcal{N}\right)\right]$ and the variance of the log-normalized intermediate purchases $var\left[\ln\left(N\left(\omega\right)/\mathcal{N}_s\left(\omega\right)\right)\right]$.