Cultural Proximity and Inter-Firm Trade[1]

Brian C. Fujiy
U.S. Census Bureau

Gaurav Khanna
UCSD

Hiroshi Toma
University of Michigan

[1] Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau.

Overview

Introduction

- Trade frictions in developing countries: Contracts, information
  - Low quality of formal institutions
  - Firms rely on informal institutions to solve these frictions
  - Cultural proximity: Codes, language, religion, ethnicity

- Example: Supplier sells rubber to shoemaker in India
  - Buyer might renege to seller $\Rightarrow$ Seller pays a cost to know buyer
  - Seller and buyer were raised in Northern India $\Rightarrow$ Information on set of values of buyer
  - Seller trusts buyer $\Rightarrow$ Lower seller cost to know buyer $\Rightarrow$ Trade

Research question

- Does cultural proximity help solve trade frictions at firm-to-firm level?
  - Use new data to provide empirical facts
  - Use a model to quantify effects: Welfare, average productivity

This paper

New datasets

1. Firm-to-firm trade dataset for a large state in India
2. Cultural endowments for firm CEOs $\Rightarrow$ Cultural proximity between firms

Empirical facts

1. $\uparrow$ Cultural proximity $\Rightarrow \uparrow$ Intensive margin (trade) + $\uparrow$ Extensive margin (matching)
2. $\uparrow$ Cultural proximity $\Rightarrow \downarrow$ Prices

Rationalizing the results

- Contracting, informational frictions in developing countries
- Cultural proximity as alternative when formal institutions work imperfectly: More trade, lower prices

Model

- Cultural proximity between firms affects costs of trade and matching
- Policy counterfactual exercises

Literature review

Cultural proximity and economic outcomes

- Trade: Boken et al. (2023); Guiso et al. (2009); Macchiavello and Morjaria (2015); Rauch (1996); Rauch and Casella (2003); Rauch and Trindade (2002); Schoar et al. (2008) || Finance: Fisman et al. (2017) || Labor markets: Hasanbasri (2019); Munshi and Rosenzweig (2016)

Production networks

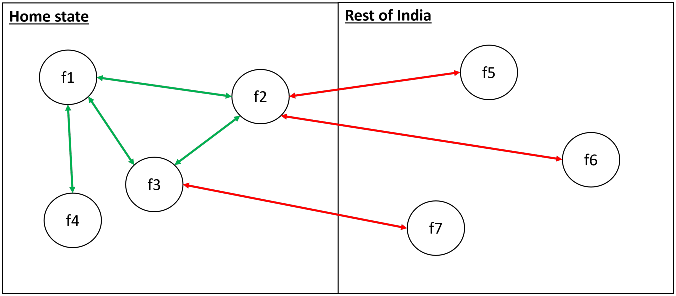
- Fontaine et al. (2023); Bernard et al. (2022); Dhyne et al. (2021); Carvalho et al. (2021); Bernard et al. (2019); Taschereau-Dumouchel (2019); Oberfield (2018); Lim (2018); Huneeus (2018); Bernard and Moxnes (2018); Antras et al. (2017); Eaton et al. (2016, 2011); Bernard et al. (2009)

$\Rightarrow$ **Contribution**: Evidence + theory on the role of cultural proximity on firm-to-firm trade

Overview

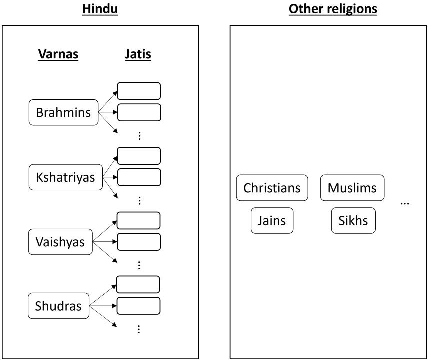
Dataset I: Firm-to-firm trade

- Daily establishment-level transactions for large Indian state, January 2019 - December 2019
- Values, quantities, implied unit prices, location, 6/8-digit HSN, seller/buyer IDs, etc.



Background: Cultural groups in India

- *Jatis* (sub-castes) or religious groups (452 cultural groups in dataset)
- Jatis are proper unit for economic analysis (Munshi, 2019)
  - Determined by occupation, tribe, language
- We treat each jati or religious group as a cultural group



Dataset II: Names of CEOs and cultural endowments

1. CEO names
   - In-state firms: State tax authority
   - Out-of-state firms: Webscrapped data from *IndiaMart*, largest B2B online platform in India
2. Cultural groups
   - Probabilistic mapping of CEO names to cultural groups
   - Webscrapped from matrimonial websites (Bhagavatula et al., 2018)
   - Cultural endowments: Probability distribution of belonging to cultural groups

$\Rightarrow$ Each CEO (firm) gets assigned a vector ρ of probabilities of belonging to each cultural group based on surname

Measuring cultural proximity

- Bhattacharyya coefficient:

$$BC\left(\boldsymbol{\rho}\left(\mathrm{s}\right),\boldsymbol{\rho}\left(\mathrm{b}\right)\right)=\sum_{x=1}^{X}\sqrt{\rho_x\left(s\right)\rho_x\left(b\right)},$$

  where $X=452$, and $\{\rho_x\left(s\right),\rho_x\left(b\right)\}$ are the probabilities of the seller s and the buyer b of belonging to cultural group x

- Full proximity: $BC=1$

- No proximity: $BC=0$

Final dataset

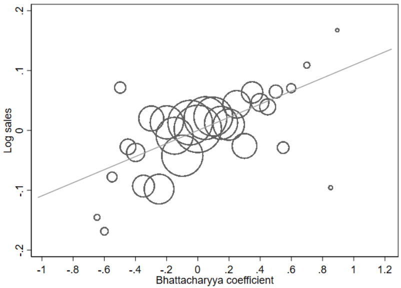
- Firm-to-firm trade dataset with firm-level cultural endowments for 2019
- 22,437 unique firms
  - 10,564 sellers / 16,990 buyers
- $\approx$ 154,000 transactions
  - Valued at 370 bln rupees $\equiv$ 5 bln USD

Overview

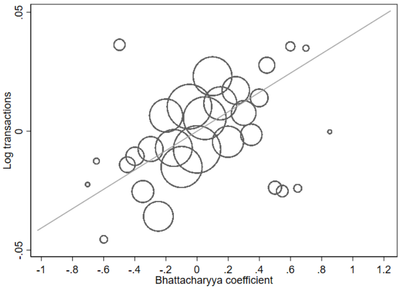
Fact 1: Cultural proximity fosters trade (intensive)

$$\ln y\left(\nu,\omega\right) = \iota_{\nu} + \iota_{\omega} + \delta BC\left(\nu,\omega\right) + \eta \ln \mathit{dist}\left(\nu,\omega\right) + \varepsilon\left(\nu,\omega\right)$$

(a) Sales



(b) # Transactions



Notes: Results residualized of seller and buyer FEs, and geographic distance. Equally distanced bins formed over the X axis. Size of bubbles represents number of transactions in each bin. The higher the Bhattacharyya coefficient, the more culturally close two firms are.

Fact 2: Cultural proximity increases likelihood to trade (extensive)

$$tr\left(\nu,\omega\right)=\iota_{\nu}+\iota_{\omega}+\delta BC\left(\nu,\omega\right)+\eta\ln dist\left(\nu,\omega\right)+\epsilon\left(\nu,\omega\right)$$

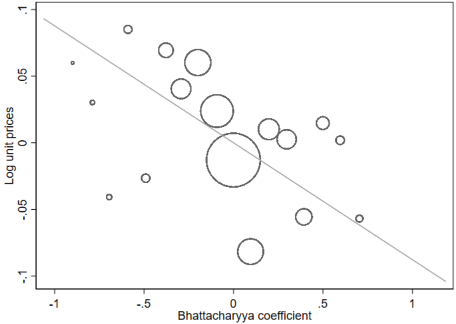
Table 1: Extensive margin, in-state-only sample

	(1)	(2)
Dep. Variable	Trade Indicator	Trade Indicator
BC	0.0009***	0.0010***
	(0.0001)	(0.0001)
Log dist.	0.0001	
	(0.0000)	
Obs.	5,606,627	5,628,290
Adj. R2	0.617	0.0106
FE	Seller, buyer	Seller, buyer, origin×dest.

Notes: Sample only contains in-state firms. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors two-way clustered at the seller and buyer level. Standard errors 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).

Fact 3: Cultural proximity lowers prices

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



Notes: Results are residualized of seller/HS, HS/month, and buyer FEs, and geographic distance. Sectors defined according to 6-digit HS classification. Equally distanced bins formed over the X axis. Size of bubbles represents number of transactions in each bin. The higher the Bhattacharyya coefficient, the culturally closer two firms are.

Cultural proximity matters for differentiated goods

- Differentiated goods
  - Rely on formal or informal contract enforcement (Nunn, 2007; Rauch, 1999)
- Classify goods into differentiated goods VS non-differentiated goods (Rauch, 1999)
- Run gravity regression at seller-buyer-good level

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

Cultural proximity matters for differentiated goods

	(1)	(2)	(3)
Dep. Variable	Log Sales	Log Sales	Log Sales
BC	0.099***	0.018	0.039
	(0.031)	(0.050)	(0.040)
$BC \times \mathbb{I}_g^{diff,con}$		0.122**	
		(0.058)	
$BC \times \mathbb{I}_g^{diff,lib}$			0.097**
			(0.047)
Obs.	174,352	174,352	174,352
Adj. R2	0.852	0.852	0.852
FE	Seller×HS, buyer, month×HS	Seller×HS, buyer, month×HS	Seller×HS, buyer, month×HS

Notes: ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Good g is defined according to 6-digit HS classification. Sales 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 two-way clustered at the seller and 4-digit HS level. Standard errors in parentheses. $\mathbb{I}_g^{diff,con}$ 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).

Cultural proximity matters for differentiated goods

	(4)	(5)	(6)
Dep. Variable	Log Sales	Log Sales	Log Sales
BC	0.069**	-0.019	0.013
	(0.027)	(0.048)	(0.038)
$BC \times \mathbb{I}_g^{diff,con}$		0.139**	
		(0.059)	
$BC \times \mathbb{I}_g^{diff,lib}$			0.095**
			(0.047)
Obs.	177,584	177,584	177,584
Adj. R2	0.853	0.853	0.853
FE	Seller×HS, buyer, month×HS, origin×dest.	Seller×HS, buyer, month×HS, origin×dest.	Seller×HS, buyer, month×HS, origin×dest.

Notes: ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Good g is defined according to 6-digit HS classification. Sales 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 two-way clustered at the seller and 4-digit HS level. Standard errors in parentheses. $\mathbb{I}_g^{diff,con}$ 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).

Cultural proximity matters for differentiated goods

- Differentiated goods require contract enforcement
- Low formal contract enforcement in India

$\Rightarrow$ Firms leverage cultural proximity when formal contract enforcement does not work

More results

Additional results

1. Cultural proximity drives complexity ▸ Complexity
2. Cultural proximity make cancellations less likely ▸ Cancellations
3. Correction for selection bias ▸ Heckman

Taste-based discrimination

1. No evidence of vertical discrimination across Varna-based hierarchy ▸ Hierarchies
2. Weaker evidence of Beckerian discrimination ▸ Firm age

Robustness

1. Results robust to cultural proximity measured by Kullback-Leibler ▸ KL
2. Results robust to inclusion of language similarity ▸ Language
3. Results not driven by Jatis' goods specialization ▸ Specialization
4. Results robust to inclusion of industry FEs ▸ Industry FEs

Overview

Model

Summary

- Bernard et al. (2022) + Cultural proximity
  - Quantitative firm-level with heterogeneous firms and endogenous network formation
- Two stages:
  1. Firms optimally chooses its set of suppliers and buyers (intensive)
  2. Given network, firms maximize profits given demand (extensive)

Setup

- Closed economy
- Continuum of firms
  - Full IO structure
  - Fixed set of firms Ω
  - Heterogeneous productivity $z(\omega)$ and cultural endowments $\boldsymbol{\rho}(\omega) = [\rho_1(\omega), \ldots, \rho_X(\omega)]$
  - Cultural proximity: $BC(\nu, \omega) = \sum_{x=1}^{X} \sqrt{\rho_\nu . \rho_\omega}$
- Households
  - Demands firms' goods
  - Inelastic labor supply
  - Income: Wages and profits

Equilibrium given network

- Technology

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

- Intermediate inputs

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

- Buyer's cost minimization $\Rightarrow$ demand for intermediates

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

- Seller's profit maximization s.t. demand for intermediates $\Rightarrow$ markup pricing

$$p(\nu, \omega) = \mu c(\nu)\, d(\nu, \omega), \quad d(\nu, \omega) \geq 1$$

- Profits:

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

Endogenous network

- Link function

$$I(\nu,\omega)=\int \mathbb{I}\left[\ln\left(\epsilon\left(\nu,\omega\right)\right)<\ln\left(\pi\left(\nu,\omega\right)\right)-\ln\left(F\left(\nu,\omega\right)\right)\right]dH\left(\epsilon\left(\nu,\omega\right)\right)$$

- Solve a fixed point algorithm to find $I(\nu,\omega)^{*}$, and equilibrium prices and allocations

Intensive margin: Gravity equation

Gravity equation

$$\ln n(\nu,\omega) = \iota + \iota_\nu + \iota_\omega + (1-\sigma)\ln d(\nu,\omega)$$

Role of cultural proximity: Trade cost

$$d(\nu,\omega) = \exp\left(\beta_1 dist(\nu,\omega) + \beta_2 BC(\nu,\omega) + \varepsilon(\nu,\omega)\right)$$

- From empirical fact 1: $\beta < 0$, if $\uparrow BC(\nu,\omega) \Rightarrow \downarrow d(\nu,\omega) \Rightarrow \uparrow n(\nu,\omega)$
- Potential microfoundations:
  - Institutional wedges (Boehm and Oberfield, 2020; Boehm, 2015)
  - Reputation (Banerjee and Duflo, 2000; Chen and Wu, 2021)
  - Loyalty (Board, 2011)

Extensive margin: Link function

Probability of matching

$$I(\nu,\omega)=\int \mathbb{I}\left[\ln\left(\epsilon\left(\nu,\omega\right)\right)<\ln\left(\pi\left(\nu,\omega\right)\right)-\ln\left(F\left(\nu,\omega\right)\right)\right]dH\left(\epsilon\left(\nu,\omega\right)\right)$$

Role of cultural proximity: Matching cost

$$F\left(\nu,\omega\right)=\kappa+\exp\left(\gamma BC\left(\nu,\omega\right)\right)$$

- From empirical fact 3: $\gamma<0$, if $\uparrow BC\left(\nu,\omega\right)\Rightarrow\downarrow F\left(\nu,\omega\right)\Rightarrow\uparrow I\left(\nu,\omega\right)$
- Potential microfoundations:
  - Information/communication frictions (Ali and Miller, 2016; Allen et al., 2019; Balmaceda and Escobar, 2017)
  - Risk-sharing (Ambrus et al., 2014; Bloch et al., 2008)

Prices

Pricing equation

$$p(\nu,\omega) = \mu c(\nu)\, d(\nu,\omega)$$

Role of cultural proximity: Trade cost

- From empirical fact 3: $\beta < 0$, if $\uparrow BC(\nu,\omega) \Rightarrow \downarrow d(\nu,\omega) \Rightarrow \downarrow p(\nu,\omega)$

Overview

Parameters I: Estimated

Cultural group probability distribution $\{\rho\}$

- Drawn from a Dirichlet distribution
- Parameters of the distribution estimated by MLE

Trade cost semi-elasticities $\{\beta_1, \beta_2\}$

- $d(\nu, \omega) = \exp(\beta_1 dist(\nu, \omega) + \beta_2 BC(\nu, \omega) + \epsilon(\nu, \omega))$
- From intensive margin regression: $\beta_1 \approx -0$, $\beta_2 = -0.03$

Matching cost semi-elasticity $\{\gamma\}$

- $F(\nu, \omega) = \kappa + \exp(\gamma BC(\nu, \omega))$
- From extensive margin regression: $\gamma = -0.13$

Parameters II: Calibrated

Other parameters

- $\alpha = 0.52$, labor cost share (Penn World Table)
- $\mu = 1.34$, markup (De Loecker et al., 2016)
  - $\sigma = 3.94$, elasticity of substitution across suppliers
- $X = 1$, normalized final demand

Parameters III: Simulated method of moments

Remaining parameters

- $\mu_{\ln(z)} = 0$, $\sigma_{\ln(z)}$, productivity distribution parameters
- $\mu_{\ln(\epsilon)}$, $\sigma_{\ln(\epsilon)}$, link function noise distribution parameters
- κ, scaling constant for pairwise matching cost
- Calibrate $\sigma_{\ln(z)}$, $\mu_{\ln(\epsilon)}$, $\sigma_{\ln(\epsilon)}$, κ by matching empirical moments

Targeted moments

- Mean and variance of log-normalized number of buyers $\ln\left(\frac{\mathcal{N}_{\boldsymbol{b}}(\nu)}{\mathcal{N}}\right)$
- Variance of log-intermediate sales-per-buyer $\ln\left(\frac{\widetilde{N}(\nu)}{\mathcal{N}_{\boldsymbol{b}}(\nu)}\right)$
- Mean of log-normalized number of sellers $\ln\left(\frac{\mathcal{N}_{\boldsymbol{s}}(\omega)}{\mathcal{N}}\right)$

Untargeted moments

- Variance of log-normalized number of sellers $\ln\left(\frac{\mathcal{N}_{\boldsymbol{s}}(\omega)}{\mathcal{N}}\right)$
- Variance of log-intermediate purchases-per-seller $\ln\left(\frac{N(\omega)}{\mathcal{N}_{\boldsymbol{s}}(\omega)}\right)$

Parameters III: Simulated method of moments

- We find $\sigma_{\ln(z)} = 0.88$, $\mu_{\ln(\epsilon)} = 64.30$,$\sigma_{\ln(\epsilon)} = 10.85$ and $\kappa = 14.80$

Table 2: Targeted and untargeted moments

Targeted moments		
	Data	Model
Mean: # of buyers	-9.24	-9.48
Variance: # of buyers	0.98	0.89
Variance: Intermediate sales	2.82	2.82
Mean: # of sellers	-9.39	-9.14
Untargeted moments		
	Data	Model
Variance: # of sellers	0.60	0.16
Variance: Intermediate purchases	2.73	0.56

Overview

Counterfactuals

- Welfare: $\mathcal{W} = \frac{w}{P}$
- Sales-weighted average productivity: $\mathcal{Z} = \left(\sum_{\nu=1}^{N} \phi_\nu z_\nu^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$
- Total sales: $\mathcal{S} = \sum_{\nu=1}^{N} S_\nu$
- Aggregate price index: $P = \left(\int_{\omega\in\Omega} p\left(\omega\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$
- Average normalized intermediate sales: $mean\left[\ln\left(\frac{\widetilde{N}(\nu)}{\mathcal{N}_b(\nu)}\right)\right]$
- Average normalized intermediate purchases: $mean\left[\ln\left(\frac{N(\omega)}{\mathcal{N}_s(\omega)}\right)\right]$
- Average normalized number of buyers: $mean\left[\ln\left(\frac{\mathcal{N}_b(\nu)}{\mathcal{N}}\right)\right]$
- Average normalized number of sellers: $mean\left[\ln\left(\frac{\mathcal{N}_s(\omega)}{\mathcal{N}}\right)\right]$

Counterfactuals

- Counterfactual 1: Social inclusion and social mixing policies
  - Going from baseline to $BC(\nu, \omega) = 1, \forall \nu, \omega$
  - Affirmative action policies to increase cultural proximity (Alan et al., 2021; Alesina et al., 2021), particularly in India (Khanna, 2020; Munshi, 2019)
- Counterfactual 2: Social isolation policies
  - Going from baseline to $BC(\nu, \omega) = 0, \forall \nu, \omega$ and $\nu \neq \omega$
  - Sociopolitical forces $\Rightarrow$ perpetuated social stratification of the caste system
- Counterfactual 3: Improving formal institutions
  - Parameters β_2 and γ shrink by 50 percent
  - Improve quality of courts (Boehm and Oberfield, 2020; Boehm, 2015) $\Rightarrow$ less reliance on cultural proximity

Counterfactuals

Table 3: Effect of cultural proximity on aggregate outcomes

	CF1: Social inclusion/mixing	CF2: Social isoliation	CF3: reducing contracting frictions
Welfare	1.76	-1.45	0.87
Avg. productivity	-0.13	0.10	-0.06
Total sales	2.76	-2.23	1.37
Avg. normalized intermediate sales	1.52	-1.20	0.76
Avg. normalized intermediate purchases	1.15	-0.94	0.57
Avg. normalized number of buyers	1.07	-0.87	0.53
Avg. normalized number of sellers	1.00	-0.82	0.50

Notes: We present the percentage gains or losses with respect 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.

Overview

Conclusions

- Cultural proximity can help solve frictions in firm-to-firm trade in developing countries
  - New datasets and quantitative model to address this channel
  - Underappreciated effects of social inclusion policies under IO economies

Cultural Proximity and Inter-Firm Trade[1]

Brian C. Fujiy
U.S. Census Bureau

Gaurav Khanna
UCSD

Hiroshi Toma
University of Michigan

[1]Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau.

[1]Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau.

References I

Alan, S., Baysan, C., Gumren, M., and Kubilay, E. (2021). Building social cohesion in ethnically mixed schools: An intervention on perspective taking. *The Quarterly Journal of Economics*, 136(4):2147–2194.

Alesina, A., Giuliano, P., and Reich, B. (2021). Nation-building and education. *The Economic Journal*, 131(638):2273–2303.

Ali, S. N. and Miller, D. A. (2016). Ostracism and forgiveness. *American Economic Review*, 106(8):2329–48.

Allen, T., Bilir, K., Chen, Z., and Tonetti, C. (2019). Knowledge diffusion through networks. *Available at SSRN 3509835*.

Ambrus, A., Mobius, M., and Szeidl, A. (2014). Consumption risk-sharing in social networks. *American Economic Review*, 104(1):149–82.

Antras, P., Fort, T. C., and Tintelnot, F. (2017). The margins of global sourcing: Theory and evidence from US firms. *American Economic Review*, 107(9):2514–64.

References II

Ash, E., Asher, S., Bhowmick, A., Bhupatiraju, S., Chen, D., Devi, T., Goessmann, C., Novosad, P., and Siddiqi, B. (2021). In-group bias in the indian judiciary: Evidence from 5 million criminal cases.

Balmaceda, F. and Escobar, J. F. (2017). Trust in cohesive communities. *Journal of Economic Theory*, 170:289–318.

Banerjee, A. V. and Duflo, E. (2000). Reputation effects and the limits of contracting: A study of the indian software industry. *The Quarterly Journal of Economics*, 115(3):989–1017.

Bernard, A. B., Dhyne, E., Magerman, G., Manova, K., and Moxnes, A. (2022). The origins of firm heterogeneity: A production network approach. *Journal of Political Economy*, 130(7):000–000.

Bernard, A. B., Jensen, J. B., Redding, S. J., and Schott, P. K. (2009). The margins of US trade. *American Economic Review*, 99(2):487–93.

Bernard, A. B. and Moxnes, A. (2018). Networks and trade. *Annual Review of Economics*, 10:65–85.

References III

Bernard, A. B., Moxnes, A., and Saito, Y. U. (2019). Production networks, geography, and firm performance. *Journal of Political Economy*, 127(2):639–688.

Bhagavatula, S., Bhalla, M., Goel, M., and Vissa, B. (2018). Cultural diversity on corporate boards and firm outcomes.

Bloch, F., Genicot, G., and Ray, D. (2008). Informal insurance in social networks. *Journal of Economic Theory*, 143(1):36–58.

Board, S. (2011). Relational contracts and the value of loyalty. *American Economic Review*, 101(7):3349–3367.

Boehm, J. (2015). The impact of contract enforcement costs onoutsourcing and aggregate productivity.

Boehm, J. and Oberfield, E. (2020). Misallocation in the market for inputs: Enforcement and the organization of production. *The Quarterly Journal of Economics*, 135(4):2007–2058.

Boken, J., Gadenne, L., Nandi, T., and Santamaria, M. (2023). Community networks and trade.

References IV

Carvalho, V., Nirei, M., Saito, Y., and Tahbaz-Salehi, A. (2021). Supply chain disruptions: Evidence from the great east japan eartquake. *The Quarterly Journal of Economics*.

Chen, M. X. and Wu, M. (2021). The value of reputation in trade: Evidence from alibaba. *The Review of Economics and Statistics*, 103(5):857–873.

Correia, S., Guimarães, P., and Zylkin, T. (2019). ppmlhdfe: Fast poisson estimation with high-dimensional fixed effects.

De Loecker, J., Goldberg, P. K., Khandelwal, A. K., and Pavcnik, N. (2016). Prices, markups, and trade reform. *Econometrica*, 84(2):445–510.

Dhyne, E., Kikkawa, A. K., Mogstad, M., and Tintelnot, F. (2021). Trade and domestic production networks. *The Review of Economic Studies*, 88(2):643–668.

Eaton, J., Jinkins, D., Tybout, J., and Xu, D. (2016). Two-sided search in international markets. In *2016 Annual Meeting of the Society for Economic Dynamics*.

References V

Eaton, J., Kortum, S., and Kramarz, F. (2011). An anatomy of international trade: Evidence from French firms. *Econometrica*, 79(5):1453–1498.

Fisman, R., Paravisini, D., and Vig, V. (2017). Cultural proximity and loan outcomes. *American Economic Review*, 107(2):457–92.

Fontaine, F., Mejean, I., and Martin, J. (2023). Frictions and adjustments in firm-to-firm trade. *mimeo*.

Guiso, L., Sapienza, P., and Zingales, L. (2009). Cultural biases in economic exchange? *The Quarterly Journal of Economics*, 124(3):1095–1131.

Hasanbasri, A. (2019). Explaining the female employment gap across religions and castes in India.

Helpman, E., Melitz, M., and Rubinstein, Y. (2008). Estimating trade flows: Trading partners and trading volumes. *Quarterly Journal of Economics*, 123(2):441–487.

Huneeus, F. (2018). Production network dynamics and the propagation of shocks.

Khanna, G. (2020). Does affirmative action incentivize schooling? evidence from india. *Review of Economics and Statistics*, 102(2):219–233.

References VI

Kone, Z. L., Liu, M. Y., Mattoo, A., Ozden, C., and Sharma, S. (2018). Internal borders and migration in india. *Journal of Economic Geography*, 18(4):729–759.

Lim, K. (2018). Endogenous production networks and the business cycle.

Macchiavello, R. and Morjaria, A. (2015). The value of relationships: evidence from a supply shock to Kenyan rose exports. *American Economic Review*, 105(9):2911–45.

Munshi, K. (2019). Caste and the Indian economy. *Journal of Economic Literature*, 57(4):781–834.

Munshi, K. and Rosenzweig, M. (2016). Networks and misallocation: Insurance, migration, and the rural-urban wage gap. *American Economic Review*, 106(1):46–98.

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

Oberfield, E. (2018). A theory of input–output architecture. *Econometrica*, 86(2):559–589.

References VII

Rauch, J. E. (1996). Trade and search: Social capital, sogo shosha, and spillovers.

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

Rauch, J. E. and Casella, A. (2003). Overcoming informational barriers to international resource allocation: Prices and ties. *The Economic Journal*, 113(484):21–42.

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

Schoar, A., Iyer, R. K., and Kumar, S. (2008). Importance of ethnic networks for business transactions of the small enterprises.

Taschereau-Dumouchel, M. (2019). Cascades and fluctuations in an economy with an endogenous production network.

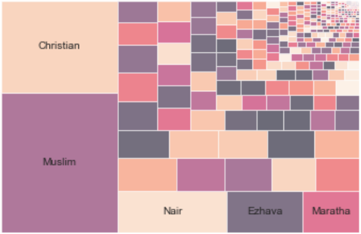
APPENDIX: Data

Example: Names of CEOs and cultural groups

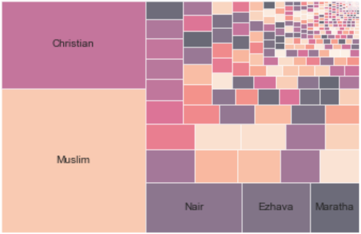
ρ	Prob(Group 1)	Prob(Group 2)	Prob(Group 3)
CEO A	0.50	0.50	0.00
CEO B	0.25	0.50	0.25
CEO C	0.00	0.00	1.00
CEO D	0.50	0.50	0.00

Total sales and purchases across cultural groups

(a) Sales



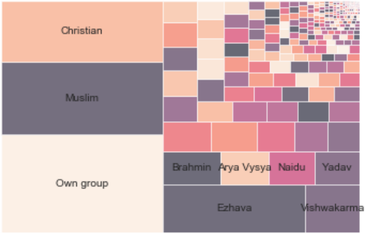
(b) Purchases



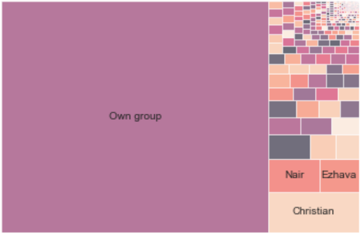
Notes: Figure shows the decomposition of the probability-weighted sales and purchases across the 452 cultural groups in our dataset.

Sales decomposition by cultural group

(a) Largest Hindu group: Nair

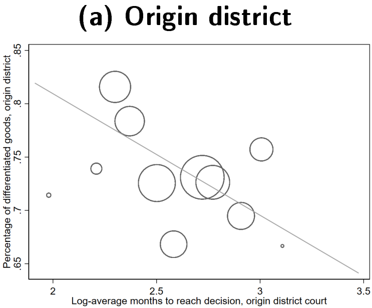


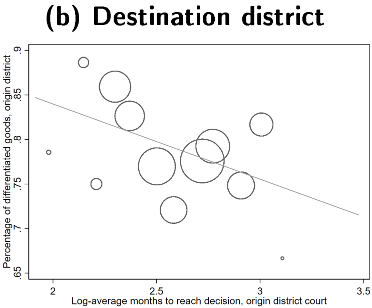
(b) Largest non-Hindu group: Muslims



Notes: Figure shows the decomposition across buyers for the largest Hindu and non-Hindu cultural groups measured by probability-weighted sales. The Nair and Muslims accounted for 4.88 and 11.83 percent of total probability-weighted sales, respectively.

Differentiated goods and court quality by district





Notes: Scatter plot at the district level. Equally distanced bins formed over the X axis. Size of bubbles represents number of observations in each bin. The larger the log-average number of months for cases to reach a decision, the worse the district's court. Differentiated goods according to the conservative classification of Rauch (1999). The log-average number of months for cases to reach a decision comes from Ash et al. (2021), where for each district court in the 2010-2018 dataset we take into account the average months in between a case's date of filing and date of decision.

APPENDIX: Regressions

Fact 1: Cultural proximity fosters trade

$$\ln y(\nu,\omega) = \iota + \iota_\nu + \iota_\omega + \delta BC(\nu,\omega) + \eta \ln dist(\nu,\omega) + \epsilon(\nu,\omega)$$

Table 4: Intensive margin

	(1)	(2)	(3)	(4)
Dep. Variable	Log Sales	Log Transactions	Log Sales	Log Transactions
BC	0.100***	0.066**	0.129***	0.076***
	(0.033)	(0.027)	(0.034)	(0.028)
Obs.	32,678	32,678	32,843	32,843
Adj. R2	0.415	0.359	0.410	0.356
FE	Seller, buyer	Seller, buyer	Seller, buyer, origin$\times$dest.	Seller, buyer, origin$\times$dest.

Notes: ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Standard errors clustered at the seller and buyer level in Columns 1 and 2. Standard errors clustered at the seller, buyer and origin-destination level in Columns 3 and 4. Origin-destination fixed effect considers the district of the seller and the buyer. The higher the Bhattacharyya coefficient, the more culturally close two firms are.

Fact 3: Cultural proximity lowers prices

$$\ln p_g(\nu, \omega, t) = \iota_{\nu \times g} + \iota_{g \times t} + \iota_\omega + \delta BC(\nu, \omega) + \eta \ln dist(\nu, \omega) + \epsilon_g(\nu, \omega, t)$$

Table 5: Prices

	(1)	(2)	(3)
Dep. Variable	Log Prices	Log Prices	Log Prices
BC	-0.069**	-0.069**	-0.066**
	(0.033)	(0.033)	(0.033)
Log dist.	0.023	0.023	0.028*
	(0.016)	(0.016)	(0.017)
Obs.	230,744	230,744	226,645
Adj. R2	0.932	0.932	0.935
FE	Seller×HS, buyer	Seller×HS, buyer, month	Seller×HS, buyer, month×HS

Notes: 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 level 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 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).

APPENDIX: Additional regressions

Alternative measure of cultural proximity

- Kullback-Leibler

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

- Symmetric Kullback-Leibler

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

Alternative measure of cultural proximity: Intensive margin

	(1)	(2)	(3)	(4)
Dep. Variable	Log Sales	Log Transactions	Log Sales	Log Transactions
KL_{sym}	-0.004***	-0.003**	-0.005***	-0.003**
	(0.001)	(0.001)	(0.002)	(0.001)
Obs.	32,678	32,678	32,843	32,843
Adj. R2	0.415	0.359	0.410	0.356
FE	Seller, buyer	Seller, buyer	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.

Notes: ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Standard errors clustered at the seller and buyer level in Columns 1 and 2. Standard errors clustered at the seller, buyer and origin-destination level in Columns 3 and 4. Origin-destination fixed effect considers the district of the seller and the buyer. A higher Kullback-Leibler divergence means two firms are socially farther away.

Hierarchies

- Generate indicator of a firm placing higher or lower than its counterpart in Varna-based hierarchy
  - Assign position based on which is the Varna or religion for which a firm has the highest probability of belonging to
  - Also consider other religions in the hierarchy: Christians, Muslims

Asymmetric effects

Dep. Variable	Log Sales	Log Transactions	Log Sales	Log Transactions
BC	0.099***	0.068**	0.129***	0.079***
	(0.034)	(0.028)	(0.035)	(0.029)
$BC \times \mathbb{I}_{\nu_{\boldsymbol{H}}\omega_{\boldsymbol{L}}}$	0.023	0.097	0.008	0.072
	(0.113)	(0.091)	(0.116)	(0.092)
$BC \times \mathbb{I}_{\nu_{\boldsymbol{L}}\omega_{\boldsymbol{H}}}$	0.045	-0.076	-0.027	-0.123
	(0.128)	(0.102)	(0.129)	(0.103)
Obs.	30,997	30,997	31,119	31,119
Adj. R2	0.418	0.360	0.412	0.357
FE	Seller, buyer	Seller, buyer	Seller, buyer, origin×dest.	Seller, buyer, origin×dest.

<u>**Notes:**</u> ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Standard errors clustered at the seller and buyer level in Columns 1 and 2. Standard errors clustered at the seller, buyer and origin-destination level in Columns 3 and 4. Origin-destination fixed effect considers the district of the seller and the buyer. 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.

Age of firms

- Hypothesis: firm sells at lower price solely because of preferences
  $\Rightarrow$ these firms exit more often
- Since no firm exist, then we use firm age
  - Test: older firms rely less on cultural proximity

Age of firms

Figure 1: Effect of cultural proximity after controlling for registration age of sellers (tax authority), intensive margin

	(1)	(2)	(3)	(4)
Dep. Variable	**Log Sales**	**Log Transactions**	**Log Sales**	**Log Transactions**
BC	0.734**	0.489*	0.800**	0.479
	(0.355)	(0.296)	(0.371)	(0.311)
Log dist.	0.070*	0.002		
	(0.040)	(0.031)		
***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
FE	Seller, buyer	Seller, buyer	Seller, buyer, origin × dest.	Seller, buyer, origin × dest.

Notes: ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors two-way clustered at the seller and buyer level. Standard errors 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). Age of seller comes from data reported in IndiaMART.

Age of firms

Figure 2: Effect of cultural proximity after controlling for establishment age of sellers (IndiaMART), intensive margin

	(1)	(2)	(3)	(4)
Dep. Variable	**Log Sales**	**Log Transactions**	**Log Sales**	**Log Transactions**
BC	0.164	0.217**	0.150	0.233**
	(0.115)	(0.094)	(0.116)	(0.097)
Log dist.	-0.044**	-0.075***		
	(0.019)	(0.014)		
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: ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors two-way clustered at the seller and buyer level. Standard errors 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). Age of seller comes from data reported by the tax authority.

Language

- Follow Kone et al. (2018)
- Common language measure between districts i and j is

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

- Language overlap measure between districts i and j is

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

Language

	(1)	(2)	(3)	(4)
Dep. Variable	Log Sales	Log Transactions	Log Sales	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: ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Standard errors two-way clustered at the seller and buyer level. Standard errors in parentheses.

Complexity

- Count how many varieties of inputs a firm buys or how many varieties of goods a firm sells.

Complexity

Dep. Variable	Log Sales	Log Sales	Log Sales	Log Sales
$BC \times varieties_{\nu}^{sold}$	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.

Notes: ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Regressions consider seller fixed effects and buyer fixed effects. Standard errors are clustered to the seller and buyer level. $varieties_{\nu}^{sold}$ and $varieties_{\nu}^{bought}$ refer to the number of varieties sold and bought by the seller divided by 10000. $varieties_{\omega}^{sold}$ and $varieties_{\omega}^{bought}$ refer to the number of varieties sold and bought by the buyer divided by 10000.

Complexity

Dep. Variable	Log Trans.	Log Trans.	Log Trans.	Log Trans.
$BC \times varieties_{\nu}^{sold}$	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: ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Regressions consider seller fixed effects and buyer fixed effects. Standard errors are clustered to the seller and buyer level. $varieties_{\nu}^{sold}$ and $varieties_{\nu}^{bought}$ refer to the number of varieties sold and bought by the seller divided by 10000. $varieties_{\omega}^{sold}$ and $varieties_{\omega}^{bought}$ refer to the number of varieties sold and bought by the buyer divided by 10000.

Specialization

- Cultural groups in India are, in many cases, defined by the production of specific goods (Munshi, 2019)
- Check if reason behind cultural proximity results is cultural groups specializing in certain goods

Specialization

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: Good g is defined according to 6-digit HS classification. Origin-destination fixed effect considers the district of the seller and the buyer. Standard errors two-way clustered at the seller and 4-digit HS level. Standard errors in parentheses. $\mathbb{I}_g^{spec,seller}$ 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.

Industry FEs

Table 6: 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)
Log dist.	-0.065***	-0.094***		
	(0.022)	(0.018)		
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: *, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Origin-destination fixed effect considers the district of the seller and the buyer. Industry classified according to the 4-digit HS classification of the most sold good by each firm. Standard errors two-way clustered at the seller and buyer level. Standard errors 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).**

Cancellations

Table 7: Cancellations

	(1)	(2)	(3)
Dep. Variable	**Dummy Cancellation**	**Dummy Cancellation**	**Dummy Cancellation**
BC	-0.006*	-0.006*	-0.006*
	(0.003)	(0.003)	(0.003)
Log dist.	-0.003*	-0.003*	-0.003
	(0.002)	(0.002)	(0.002)
Obs.	252,191	252,191	248,192
Adj. R2	0.102	0.102	0.110
FE	Seller×HS, buyer	Seller×HS, buyer, month	Seller×HS, buyer, month×HS

Notes: *, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Good g is defined according to 6-digit HS classification. Sales 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 two-way clustered at the seller and 4-digit HS level. Standard errors 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).**

Correction for selection bias

- Problem: Endogenous network $\Rightarrow$ bias when estimating trade elasticities
- Solution: Follow Helpman et al. (2008) $\Rightarrow$ Heckman selection model
- Steps:
  1. First stage probit:

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

  2. Latent variable:

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

  3. Mills ratio:

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

  4. Second stage:

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

Correction for selection bias

Table 8: Correction for selection bias, second stage

	(1)	(2)	(3)	(4)
Dep. Variable	**Log Sales**	**Log Transactions**	**Log Sales**	**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 $\times$ dest.	Seller, buyer, origin $\times$ dest.	Seller, buyer, origin $\times$ dest.	Seller, buyer, origin $\times$ dest.

Notes: Columns 1 and 2 do not consider the correction for selection bias term. Sample contains only in-state firms. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Standard errors two-way clustered at the seller and buyer level. Standard errors 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).

Fixed point iteration algorithm

1. Guess the link function
2. Given a link function, iterate over $P(z)^{1-\sigma}$ until achieving convergence
3. Given a link function and $P(z)^{1-\sigma}$, iterate over $S(z)$ until achieving convergence
4. Given $P(z)^{1-\sigma}$ and $S(z)$, calculate the link function again
   - If the new link function is close to the guess, stop
   - If the new link function is far from the guess, update and iterate

APPENDIX: Parameter estimation

Cultural endowments: Dirichlet distribution

- 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
- $\rho_\nu(1), \ldots, \rho_\nu(452) \sim \mathcal{D}(\alpha_1, \ldots, \alpha_{452})$, $\alpha_1, \ldots, \alpha_{452} > 0$
- Probability density function for the Dirichlet distribution is

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

where

- $\rho_\nu(x) \in [0, 1]$
- $\sum_{x=1}^{452} \rho_\nu(x) = 1$
- $\Gamma(.)$ is the gamma function
- $\frac{\Gamma\left(\sum_{x=1}^{452} \alpha_x\right)}{\prod_{x=1}^{452} \Gamma(\alpha_x)}$ is a normalization constant

Cultural endowments: Dirichlet distribution

- Estimate the vector $\boldsymbol{\alpha} = \left[\begin{array}{ccc} \alpha_1, & \ldots, & \alpha_{452} \end{array}\right]$ by maximum likelihood
- Let $\boldsymbol{\varrho} = \{\boldsymbol{\rho}_1, \ldots, \boldsymbol{\rho}_\mathrm{N}\}$, where $\mathcal{N}$ is the total number of firms
- Log-likelihood function

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

Gravity equation

- From theoretical model

$$\ln n(\nu,\omega) = \iota + \iota_\nu + \iota_\omega + (1-\sigma)\ln d(\nu,\omega)$$

$$d(\nu,\omega) = \exp\left(\beta_1 dist(\nu,\omega) + \beta_2\left(BC(\nu,\omega) - 1\right)\right)$$

- From the intensive margin regressions we estimate

$$\ln n(\nu,\omega) = \iota + \iota_\nu + \iota_\omega + \delta BC(\nu,\omega) + \gamma \ln dist(\nu,\omega) + \epsilon(\nu,\omega)$$

- Then

$$(1-\sigma)\beta_1 = \widehat{\gamma}, (1-\sigma)\beta_2 = \widehat{\delta}$$

- With $\sigma = 3.94$ we find $\beta_1 \approx 0$, $\beta_2 = -0.02$

Matching cost

- $F(\nu,\omega) = \exp(\gamma BC(\nu,\omega))$
- 1st step: Run regression

$$\ln n(\nu,\omega) = \iota_\nu + \iota_\omega + \delta BC(\nu,\omega) + \gamma \ln(dist(\nu,\omega)) + \varepsilon(\nu,\omega)$$

- 2nd step: Run probit regression

$$I(\nu,\omega) = \int 1\left[\ln(\epsilon(\nu,\omega)) < \ln \widehat{n(\nu,\omega)} - \ln(\sigma) - \gamma BC(\nu,\omega)\right] dH(\epsilon(\nu,\omega))$$

Matching cost

Table 9: Second stage estimation for matching cost

Dep. Variable	Trade Indicator
BC	0.131^{***}
	(0.008)
Obs.	5,606,627
Pseudo R2	0.453

Notes: We winsorize $\ln \widehat{n\left(z,z'\right)}$ at 1% and 99%. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Standard errors in parentheses. Sample only contains firms in-state.