Cultural Proximity and Production Networks

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Overview

Introduction

1. Frictions in trade: Contracts, information
2. In developing countries: Firms rely on informal institutions to solve these frictions
   - Cultural proximity: Codes, language, religion, ethnicity
3. Example: Supplier sells rubber to shoemaker
   - Supplier does not know if shoemaker will pay
   - Supplier and shoemaker were raised in Northern India $\Rightarrow$ Information on set of values of shoemaker
   - Supplier trusts shoemaker $\Rightarrow$ Trade

Research question

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

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

Theoretical model

- Cultural proximity between firms affects costs of trade and matching

Counterfactuals

- Aggregate implications of cultural (i) autarky and (ii) full trade

Literature review

Cultural proximity and economic outcomes

- Trade: 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

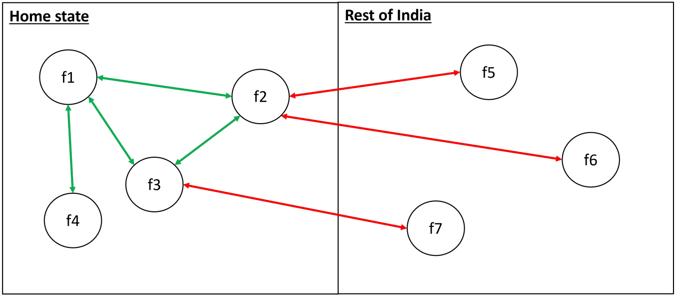
- Antras et al. (2017); Bernard et al. (2009, 2019); Bernard and Moxnes (2018); Bernard et al. (2022); Dhyne et al. (2021); Eaton et al. (2011, 2016); Huneeus (2018); Lim (2018); Oberfield (2018); Taschereau-Dumouchel (2019)

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

Overview

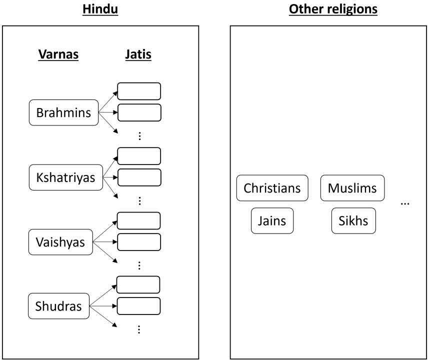
Dataset I: Firm-to-firm trade

- 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 surnames 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 $\boldsymbol{\rho}$ of probabilities of belonging to each cultural group based on surname

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

Measuring cultural proximity

- Bhattacharyya coefficient:

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

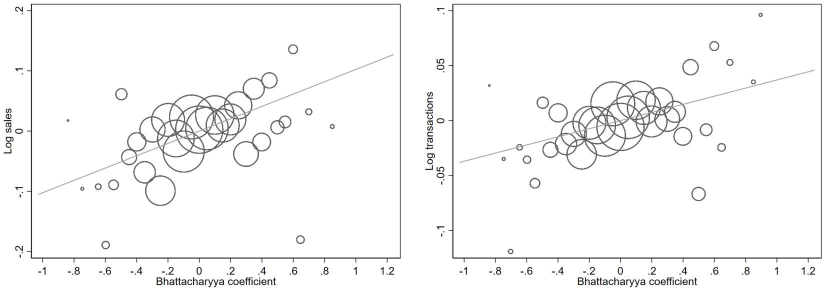
  where $X = |\mathcal{X}| = 452$, and $\{\rho_x\left(s\right), \rho_x\left(b\right)\}$ are the probabilities of the seller s and the buyer b of belonging to cultural group x

- Full proximity: $BC = 1$

- No proximity: $BC = 0$

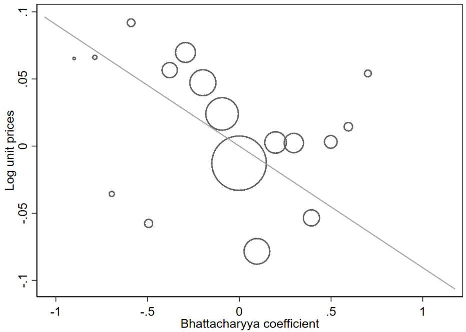
Fact 1: Cultural proximity fosters trade

(a) Sales (b) # Transactions



Notes: Results residualized of seller FEs, buyer FEs and log 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 lowers prices



Notes: Results residualized of seller FEs, HS code FEs and log 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 more culturally close two firms are.

Fact 3: Cultural proximity increases likelihood to trade

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

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

Dep. Variable	Trade Dummy
BC	0.00088***
	(0.00008)
Obs.	5,855,123
Adj. R2	0.00872

Notes: Sample only contains in-state firms. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Regressions consider seller FEs and buyer FEs. Standard errors are clustered to the seller and buyer level. The higher the Bhattacharyya coefficient, the more culturally close two firms are.

Additional results

1. Cultural proximity matters when seller and buyer are of the same size
   - Stronger effect when both firms are large
   - Proximity less relevant when seller and buyer are of different size

2. No evidence of vertical discrimination across Varna-based hierarchy
   - No asymmetric effect of cultural proximity for higher-placed firm with lower-placed firm

Size Discrimination

Discussion of results

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: Trade costs, matching costs
- Cultural proximity as solution when markets work imperfectly: More trade, lower prices

Overview

Environment: Bernard et al. (2022) + Cultural proximity

- Closed economy
- Continuum of firms
  - Roundabout production economy
  - Fixed set of firms Ω
  - Heterogeneous productivity $z(\omega)$
- Cultural endowments

$$\boldsymbol{\rho}(\omega) = [\rho_1(\omega), \ldots, \rho_X(\omega)]', \forall \omega$$

- Cultural proximity

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

- Households
  - Inelastic labor supply
  - Income: Wages and profits

Intensive margin: Gravity equation

- Gravity equation

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

where

- $n(\nu, \omega)$ are the sales
- $d(\nu, \omega)$ is the trade cost

Role of cultural proximity: Trade cost

$$d(\nu, \omega) = \exp(\beta(BC(\nu, \omega) - 1)), \quad \beta < 0$$

- From empirical fact 1: $\beta < 0$, if $\uparrow BC(\nu, \omega) \Rightarrow \downarrow d(\nu, \omega) \Rightarrow \uparrow n(\nu, \omega)$

Extensive margin: Link function

- Link function: Probability of matching

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

  where
  - $I(\nu,\omega)$ is the probability of matching
  - $\pi(\nu,\omega)$ are the profits
  - $F(\nu,\omega)$ is the cost of matching
  - $\epsilon \overset{iid}{\sim}$ log-normal

Role of cultural proximity: Matching cost

$$F(\nu,\omega) = \exp(\gamma BC(\nu,\omega)), \quad \gamma < 0$$

- From empirical fact 3: $\gamma < 0$, if $\uparrow BC(\nu,\omega) \Rightarrow \downarrow F(\nu,\omega) \Rightarrow \uparrow I(\nu,\omega)$

Prices

- Profit maximization of sellers s.t. demand yields

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

where

- $\mu \equiv \frac{\sigma}{\sigma-1}$ is the markup
- $c(\nu) = \frac{P(\nu)^{1-\alpha}}{z(\nu)}$ is marginal cost
- $P(\omega) \equiv \left(\int_{\nu\in\Omega(\omega)} p(\nu,\omega)^{1-\sigma}\, d\nu\right)^{\frac{1}{1-\sigma}}$ is a price index
- $\Omega(\omega)$ is the *endogenous* set of suppliers of ω
- $d(\nu,\omega) = \exp(\beta(BC(\nu,\omega)-1)), \quad \beta < 0$

Role of cultural proximity: Trade cost

- From empirical facts 1 and 2: $\beta < 0$, 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 $\{\beta_1, \beta_2\}$

- $d(\nu, \omega) = \exp(\beta_1 dist(\nu, \omega) + \beta_2 (BC(\nu, \omega) - 1) + \epsilon(\nu, \omega))$
- From intensive margin regression: $\beta_1 \approx 0$, $\beta_2 = -0.02$

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

- $F(\nu, \omega) = \exp(\gamma BC(\nu, \omega))$
- From extensive margin regression: $\gamma = -0.07$

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
- Calibrate $\sigma_{\ln(z)}$, $\mu_{\ln(\epsilon)}$, $\sigma_{\ln(\epsilon)}$ by matching empirical moments

Targeted moments

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

Untargeted moments

- Mean and variance of log-normalized number of sellers $\ln\left(\frac{\mathcal{N}_s(\omega)}{\mathcal{N}}\right)$
- Variance of log-intermediate purchases-per-seller $\ln\left(\frac{N(\omega)}{\mathcal{N}_s(\omega)}\right)$

Parameters III: Simulated method of moments

- We find $\sigma_{\ln(z)} = 0.97$, $\mu_{\ln(\epsilon)} = 57.59$ and $\sigma_{\ln(\epsilon)} = 9.68$

Table 2: Targeted and untargeted moments

Targeted moments		
	Data	Model
$mean\left[\ln\left(\mathcal{N}_b(\nu)/\mathcal{N}\right)\right]$	-9.02	-9.02
$var\left[\ln\left(\mathcal{N}_b(\nu)/\mathcal{N}\right)\right]$	1.33	1.33
$var\left[\ln\left(\widetilde{N}(\nu)/\mathcal{N}_b(\nu)\right)\right]$	3.04	3.04
Untargeted moments		
	Data	Model
$mean\left[\ln\left(\mathcal{N}_s(\omega)/\mathcal{N}\right)\right]$	-9.14	-8.52
$var\left[\ln\left(\mathcal{N}_s(\omega)/\mathcal{N}\right)\right]$	0.93	0.21
$var\left[\ln\left(N(\omega)/\mathcal{N}_s(\omega)\right)\right]$	3.12	0.59

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 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: Each firm belongs to a different cultural group
  - Going from baseline to $BC(\nu, \omega) = 0$ for all ν, ω and $\nu \neq \omega$
  - To measure pervasive effect of cultural proximity

- Counterfactual 2: Every firm belongs to the same cultural group
  - Going from baseline to $BC(\nu, \omega) = 1$ for all ν, ω
  - To measure how cultural proximity solves frictions

Counterfactual results

Table 3: Change relative to baseline

	CF1: Each firm belongs to a different cultural group	CF2: All firms belong to the same cultural group
Welfare	-1.33%	1.61%
Total sales	-2.65%	3.29%
Aggregate price index	1.34%	-1.58%
Average normalized number of buyers	-0.68p.p.	0.85p.p.
Average normalized number of sellers	-0.62p.p.	0.76p.p.
Sales-weighted average productivity	0.11%	-0.13%

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

Changes in sales generate changes in average productivity

Table 4: Change in sales by productivity quartiles

	CF1: Each firm belongs to a different cultural group	CF2: All firms belong to the same cultural group
4th quartile (most productive)	-2.63%	3.26%
3rd quartile	-2.78%	3.46%
2nd quartile	-2.75%	3.46%
1st quartile (least productive)	-2.76%	3.42%

Notes: We aggregate the sales of all firms that belong to a productivity quartile and calculate their percentage variation with respect to the baseline.

Overview

Conclusions

- Cultural proximity can help solve frictions in firm-to-firm trade
  - New datasets and quantitative model to address this channel
  - Higher cultural proximity: More sales, more matches, lower prices

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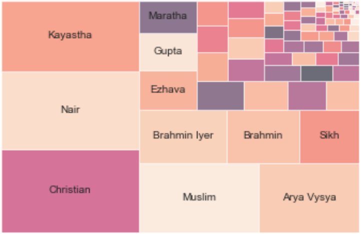
APPENDIX: Data

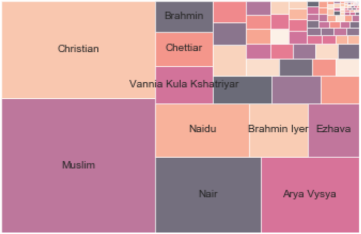
Example: Names of CEOs and cultural groups

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



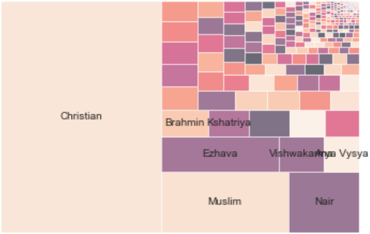
(a) Sales



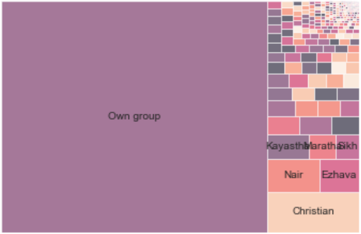
(b) Purchases

Sales decomposition by cultural group

(a) Largest Hindu group: Nair



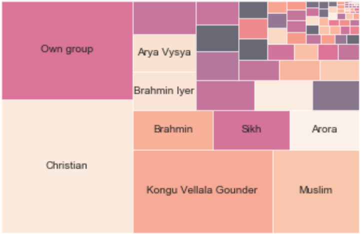
(b) Largest non-Hindu group: Christians



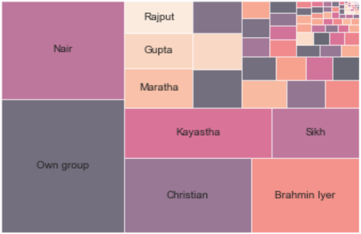
Notes: The Nair and Christians accounted for 12.83 and 13.87 percent of total sales, respectively.

Purchases decomposition by cultural group

(a) Largest Hindu group: Nair



(b) Largest non-Hindu group: Muslims



Notes: The Nair and Muslims accounted for 9.64 and 24.91 percent of total purchases, respectively.

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 5: Intensive margin

	(1)	(2)
	Log Sales	Log Transactions
BC	0.097***	0.033*
	(0.036)	(0.018)
Obs.	32,773	32,773
Adj. R2	0.439	0.309

Notes: ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Regressions consider seller FEs and buyer FEs. Standard errors are clustered to the seller and buyer level. The higher the Bhattacharyya coefficient, the more culturally close two firms are.

Fact 2: Cultural proximity lowers prices

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

Table 6: Prices

	(1)	(2)	(3)
BC	-0.084***	-0.073**	-0.052*
	(0.031)	(0.029)	(0.030)
Obs.	262,619	259,148	257,516
Adj. R2	0.815	0.859	0.878
FE	Seller, HS	Seller × HS	Seller × HS, Buyer

Notes: Sector *s* is defined according to 6-digit HS classification. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Standard errors are clustered at the seller and HS level. The higher the Bhattacharyya coefficient, the more culturally close two firms are.

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)
	Log Sales	Log Transactions
KL_{sym}	-0.004**	-0.001*
	(0.002)	(0.001)
Obs.	32,773	32,773
Adj. R2	0.641	0.559

Notes: ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Regressions consider seller FEs and buyer FEs. Standard errors are clustered to the seller and buyer level. The lower the symmetric Kullback-Leibler measure, the more culturally close two firms are.

Alternative measure of cultural proximity: Prices

	(1)	(2)	(3)
KL_{sym}	0.005***	0.004***	0.002*
	(0.001)	(0.001)	(0.001)
Obs.	262,619	259,148	257,516
Adj. R2	0.815	0.859	0.878
FE	Seller, HS	Seller $\times$ HS	Seller $\times$ HS, Buyer

Notes: Sector s is defined according to 6-digit HS classification. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Standard errors are clustered at the seller and HS level. The lower the symmetric Kullback-Leibler measure, the more culturally close two firms are.

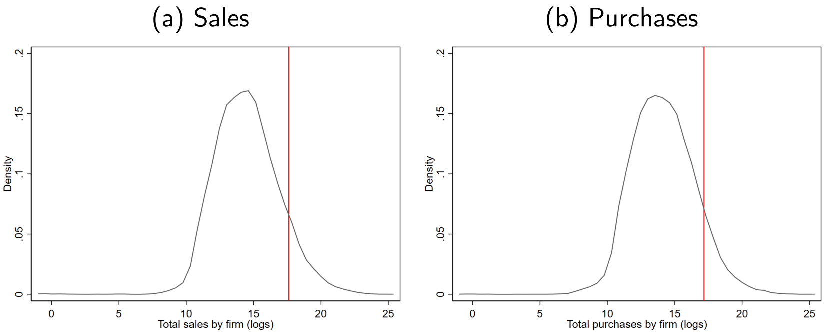
Alternative measure of cultural proximity: Extensive margin

Dep. Variable	Trade Dummy
KL_{sym}	-0.00004***
	(0.00000)
Obs.	5,855,123
Adj. R2	0.00871

Notes: Sample only contains in-state firms. ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Regressions consider seller FEs and buyer FEs. Standard errors are clustered to the seller and buyer level. The lower the symmetric Kullback-Leibler measure, the more culturally close two firms are.

Size of firms

- Classify a firm as large if it belongs to the top decile of sales or purchases



Notes: Vertical lines denote the 90th percentile cutoff. Firms to the right of the threshold are considered large.

Size of firms

	(1)	(2)
	Log Sales	Log Transactions
$BC \times \mathbb{I}_{\nu_S \omega_S}$	0.199***	0.063**
	(0.058)	(0.029)
$BC \times \mathbb{I}_{\nu_L \omega_L}$	0.280***	0.082**
	(0.067)	(0.032)
$BC \times \mathbb{I}_{\nu_L \omega_S}$	-0.029	-0.013
	(0.055)	(0.029)
$BC \times \mathbb{I}_{\nu_S \omega_L}$	-0.123	0.003
	(0.076)	(0.039)
Obs.	32,773	32,773
Adj. R2	0.439	0.309

Notes: ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Regressions consider seller FEs and buyer FEs. Standard errors are clustered to the seller and buyer level. The higher the Bhattacharyya coefficient, the more culturally close two firms are. The subindex that accompanies ν denotes the size of the seller, while the subindex that accompanies ω denotes the size of the buyer. S denotes a small firm and L denotes a large firm.

Size of firms

	(1)	(2)	(3)	(4)
	Log Sales	Log Sales	Log Transactions	Log Transactions
BC	0.083*	0.064	0.042	0.018
	(0.049)	(0.043)	(0.026)	(0.022)
$BC \times \mathbb{I}_{\nu_L}$	0.022		-0.013	
	(0.066)		(0.033)	
$BC \times \mathbb{I}_{\omega_L}$		0.079		0.038
		(0.066)		(0.033)
Obs.	32,773	32,773	32,773	32,773
Adj. R2	0.642	0.642	0.559	0.559

Notes: ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Regressions consider seller FEs and buyer FEs. Standard errors are clustered to the seller and buyer level. The higher the Bhattacharyya coefficient, the more culturally close two firms are. ν_L denotes the seller is large while ω_L denotes the buyer is large.

Asymmetric effects

- 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

	(1)	(2)
	Log Sales	Log Transactions
BC	0.098***	0.032*
	(0.037)	(0.019)
$BC \times \mathbb{I}_{\nu_H \omega_L}$	0.011	0.070
	(0.130)	(0.061)
$BC \times \mathbb{I}_{\nu_L \omega_H}$	0.003	-0.073
	(0.142)	(0.068)
Obs.	31,305	31,305
Adj. R2	0.646	0.561

Notes: ***, ** and * indicate statistical significance at the 99, 95 and 90 percent level respectively. Regressions consider seller FEs and buyer FEs. Standard errors are clustered to the seller and buyer level. The higher the Bhattacharyya coefficient, the more culturally close two firms are. 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.

APPENDIX: Theoretical model

Firms

- Continuum of firms with technology

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

- Intermediate inputs

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

- Pricing schedule

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

- Demand for intermediates

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

Households

- Representative household solves

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

- Demand for final goods

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

Equilibrium

- Price index of all of the goods acquired by firm $z^{'}$

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

- Total sales of firm z

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

- Link function

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

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 $\boldsymbol{\varrho} = \{\boldsymbol{\rho_1}, \ldots, \boldsymbol{\rho_N}\}$, 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

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

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

- 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 PPML regression

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

- 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 7: Second stage estimation for matching cost

	(1)
	Probit
BC	0.076***
	(0.010)
$\ln \widehat{n(z, z')}$	0.095***
	(0.001)
Constant	-3.343***
	(0.010)
Obs.	5,855,126
Pseudo R2	0.053

Notes: We winsorize $\ln \widehat{n(z, z')}$ 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.