Community Networks and Trade

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Abstract

Do community networks shape firm-to-firm trade in emerging economies? We study the role of communities (castes) in facilitating firm-to-firm trade and firm growth using data on firm-to-firm transactions and firm owners’ community affiliations for the universe of medium- and large- sized firms in West Bengal, India. We find that firms are substantially more likely to trade, and trade more, with firms from their own caste. Studying the mechanisms underlying this effect of communities on trade, we find evidence consistent both with castes alleviating trade frictions and taste-based discrimination by firms against those outside their community. Guided by these stylized facts, we develop a model of firm-to-firm trade in which communities affect match productivity and matching costs. We estimate the model parameters and find that belonging to the same community leads to more profitable matches and substantially lower matching costs. Removing all across-caste trading frictions would almost double the number of firm-to-firm trade relationships and would increase average firm size by 34%.

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1 Introduction

Most firms in the developing world are small, which limits their capacity to innovate, export or even survive (Hsieh and Olken, 2014; Ciani et al., 2020). There is growing evidence that a key determinant of firm growth is their production network: the clients and suppliers firms trade with are a key determinant of firm size (Bernard et al., 2022), productivity (Atkin et al., 2017; Antrás et al., 2017; Alfarо-Ureña et al., 2022) and access to credit (McMillan and Woodruff, 1999). Yet we know very little about the determinants of firms’ production networks in developing countries.

One potential such determinant is communities. A large literature has shown that internal cooperation within communities supports domestic economic networks, and facilitates firms’ access to credit (Fisman et al., 2017), investors (Hjort, 2021), insurance (Mazzocco and Saini, 2012) and workers (Munshi and Rosenzweig, 2016). Cross-country immigrant communities shape export flows across countries (Greif, 1993; Gould, 1994; Rauch, 2001), particularly in the context of high contractual frictions (Rauch and Trindade, 2003). Communities could similarly facilitate economic interactions in firm-to-firm networks in developing countries, where such frictions loom large.

This paper considers the role of community networks in India in shaping firm-to-firm trade. Using panel data on firm-to-firm transactions and information on the firm owner’s community, we find that two firms are substantially more likely to trade, and trade more, when they belong to the same community. We provide evidence consistent both with communities alleviating frictions and with taste-based discrimination. To understand the aggregate effects of communities on the economy via trade, we build a model of network formation in which communities affect both the productivity of a client-supplier relationship and the cost of forming the relationship. We find that allowing all firm-pairs to enjoy the higher efficiency and lower-matching cost of within-caste relationships would nearly double the number of trading relationships, and lead to firm growth.

Our first contribution is to systematically document the effect of caste net-
works on firm-to-firm trade and provide evidence on the mechanisms underlying this effect. To do so, we use administrative data on the universe of firms paying Valued-Added-Taxes (VAT) in the state of West Bengal, India, between 2010 and 2016 which enables us to overcome two key observational constraints. First, the data contains annual transactions between firms, enabling us to map firms’ production networks. Second, by searching firms in the official registries using their tax identification numbers, we obtain the firm owners’ names for the majority of firms. We then assign each last name to a \textit{jati} using the anthropological literature (Singh, 1996): jatis (or castes) are the bedrock of India’s social architecture and support economic and social networks (Munshi, 2019). Our data contains 106,775 firms in 723 castes, and over 200 million potential trade relationships.

We find large effect of castes on trade, both at the extensive and intensive margin. Firms within caste networks are likely to make similar industry and location choices, and experience correlated shocks, so we control flexibly for the joint locations and products sold by suppliers and clients, and allow for arbitrary shocks to all trading parties over time. We find that being in the same caste doubles the probability that two firms trade, and, when they do, increases trade volumes by close to 20%.

Why do castes affect firm-to-firm trade? Our second contribution is to shed some light on the mechanisms that underlie the effects of castes on trade. We first consider whether our estimates of caste effects on trade are larger for trading relationships where we expect frictions to be more severe, following Boehm and Oberfield (2020) in our choice of proxies for the strength of frictions in the Indian context. We find that castes matter more for the trade of products that are relationship-specific (Rauch and Trindade, 2003), for whom the hold-up problem is more of a concern, and when trading partners are located in areas with worse-performing contracts, making the formal enforcement of contracts harder. We then consider whether part of the effect of caste could be due to taste-based discrimination by firms against those outside their caste. We test for Becker (1957)’s argument that firms with strong discriminatory preferences will eventually be forced out of competitive markets, by looking at the survival rate of firms as a function of their within-caste preferences, in the spirit of Weber and Zulehner (2014). We find that firms with high preferences for trading with their caste, relative to their industry average, are indeed more likely to exit. Finally, we find no
evidence of inaccurate (or biased) statistical discrimination in our context.

Our third contribution lies in the quantification of the effect of castes on the aggregate economy. To do this, we build on the quantitative trade model developed by Bernard et al. (2022) that features a continuum of firms with heterogeneous productivity and matching-ability and endogenous match formation. This model can explain the main patterns of firm-to-firm networks: (i) high dispersion in sales and number of connections, (ii) positive correlation between number of clients and sales and (iii) negative degree assortativity. In the model, each firm uses labour and an input bundle sourced from other firms, to produce a differentiated variety. Firms choose who to match with, by comparing the potential profits of the match with the matching-cost. Firms that can source from more suppliers enjoy a lower input price index, and sell more.

We extend this framework to allow for a third source of heterogeneity coming from the firm’s community (caste) affiliation. Castes may matter for two reasons. First, we allow castes to affect the efficiency in trading (i.e., lower risk or information frictions, higher trust). Thus, conditional on a match, sales between two firms in the same castes feature an additional caste efficiency-effect, conditional on buyer and supplier characteristics. Firms trading within their caste also face a caste-specific matching cost. Importantly, the probability that two firms trade will be affected by their caste via both channels: the potential profits of the match is determined by the efficiency caste-effect, while the matching cost includes a caste component.

We follow the strategy in Bernard et al. (2022) and estimate the model parameters using the Simulated Method of Moments. We estimate five parameters: the variance of productivity, the mean and variance of relationship capability, the caste efficiency effect and the caste matching cost. While the estimation of all parameters is simultaneous, we use our reduced form evidence on the effect of castes on the intensive and extensive margins of trade as moments to estimate the caste-specific parameters. We find that castes increase both trading efficiency and matching ability. Firm-pairs in the same caste are 6.8 percent more efficient when trading and face matching costs that are fifteen times lower than firm-pairs across communities. Importantly, we show that both parameters are necessary: a model including only an efficiency caste parameter, or only a matching-cost caste
parameter, is unable to replicate our reduced form results.

Finally, we use our estimated model to study how communities shape aggregate outcomes such as firm size, firm connections and welfare. We perform two counterfactuals. We ask: What would be the aggregate implications of allowing all firm-pairs to benefit from the higher efficiency and the lower matching costs that firms in the same castes face? We find that expanding community-affiliation to all firms has very large aggregate effects. Welfare in the economy goes up by 93%. This comes from an 87% increase in total firm-to-firm connections, and an input price reduction of almost 20%. As a result of the increased trading efficiency and the lower matching costs, average firm size (network sales) grows by 34%. The large magnitude of the results can be explained by the fact that we expand community affiliation to 96% of firm-pairs (same-caste pairs represent only 3.6% of all potential pairs in our data). In a second counterfactual we explore the aggregate effects of eliminating all caste affiliations, by “switching off” both caste effects. We find that this would lead to marginally lower firm connections (2.4% decrease) and a 3.7% decrease in welfare. Our results suggest that allowing more firms to benefit from the higher efficiency and lower matching cost enjoyed by communities would have large aggregate implications.

The rest of the paper is organized as follows. Section 2 describes our context of study, highlighting the role of castes in shaping economic outcomes in India, and the data we use. Section 3 presents new stylized facts on the effect of community networks on trade and evidence regarding the mechanisms underlying these effects. Section 4 presents our model, section 5 our model estimation strategy and results, whilst section 6 discusses counterfactuals.

2 Context and data

Our context of study is West Bengal, a large Indian state with 90 million inhabitants and a GDP per capita of 8200 ppp USD in 2020, similar to the all-India average. Our period of study is 2010-2016.
2.1 Community networks in India

India’s social architecture is organized around thousand castes or *jatis*. Internal cooperation within castes supports economic networks: marriage are typically within castes, informal loans and insurance mechanisms are concentrated within castes and castes historically determined individuals’ occupation and location choices (see Munshi, 2019, for a review of the role of caste in Indian society). Whilst the concept of caste originates in Hinduism, it has extended across other religions, with non-Hindu castes playing a similar role as Hindu castes in Indian society today (Cassan, 2020).

There is evidence that caste networks help alleviate market frictions in credit markets (Fisman et al., 2017), labor markets (Munshi and Rosenzweig, 2016) and insurance markets (Mazzocco and Saini, 2012): cultural proximity between caste members reduces asymmetric information, allowing transactions to occur in contexts with severe informational and contractual frictions and thereby increasing market efficiency. The existence of caste networks could however simultaneously lead to individuals transacting more within caste for preference-based reasons, leading to discrimination and ultimately resource misallocation as individuals’ economic opportunities are constrained if they do not belong to the ‘right’ caste. Caste networks have been shown to lead to such inefficiencies in capital markets (Banerjee and Munshi, 2004), groundwater trade (Anderson, 2011) and education decisions (Munshi and Rosenzweig, 2006).

2.2 Data on production networks

We consider how caste networks shape firm-to-firm trade by using detailed data on firm-to-firm transactions matched with information on firm owner’s caste. We use administration data on firm-level tax returns and tax registration information obtained from the West Bengal Directorate for Commercial Taxes for the fiscal years 2010-2011 to 2015-2016, containing information on the universe of all firms paying Valued-Added-Taxes (VAT) to the state over the period.

The tax returns data contains information on all transactions between firms paying VAT in West Bengal: both firms involved in the transaction report the annual transaction amount as well as the tax identification number of their client or supplier. The tax registration data contains information on firms’ locations
(1088 unique postcodes) and the products sold by the firms which we classify using India’s National Industry Classification (NIC) into 162 product codes. For 77% of firms in our data the product codes are available at the detailed 4-digit level, for the remaining we use 3-digit codes. Controlling for detailed product information affects the interpretation of our estimates of caste effects on trade so we present robustness checks using only firms for which detailed product level information is available below. This data is described in more details in Gadenne et al. (2022).

2.3 Other data

We use several other datasets to consider whether castes play a different role for trading relationships facing more severe contractual frictions. To proxy for the difficulty of enforcing contracts legally, we construct a measure of local court congestion. We use data on 2.6 million cases from District and Session courts in West Bengal between 2010 and 2018, collected from the Indian e-courts platform by Ash et al. (2021). Each case record includes information on the court’s district, the filing date and, if applicable, the decision date. Our preferred measure of court congestion is an indicator of whether a case had been decided two years after being filed. We aggregate these into an ex-post probability that a case filed in a given district and fiscal year would be decided within the next two years. We consider court congestion in the buyer’s district, in 57% of cases the seller and the buyer are located in the same district.

We also consider whether castes affect trade in relationship-specific products differently. We use the classification in Rauch (1999) to characterize all products as either homogeneous (traded on an organized exchange or with a reference price) or relationship specific. For our measure of goods’ relationship-specificity, we use the concordance tables from Liao et al. (2020) to obtain the share of relationship-specific inputs within each NIC 4-digit code.\(^2\)

2.4 Variable and sample creation

Our main variable of interest is an indicator for whether two firm owners belong to the same caste community. Firms’ tax identification number is public knowl-

\(^2\)We concord from the original SITC Rev 2 codes to NIC via 6-digit NAICS codes
edge in India, information on the firm owner’s name can be obtained by querying the firm ID on a public database. We follow Cassan et al. (2021) in using the systematic classification of Indian last names into various tribes and communities, including 2,205 castes (or ‘main communities’) developed by the People of India project in their 1985 Anthropological Survey of India (Singh, 1996). The merge between last names and castes is sometimes not unique: 49% of firm owners’ last names in our data are associated with more than one caste. When this occurs, we allocate the first caste in alphabetical order to each last name. We discuss the robustness of our results to alternative methods of allocating last names to a caste below. Using this method, we obtain information on the firm owner’s caste for 75% of firms in the administrative tax data.

Our final firm-level sample consists of 106,775 firms allocated to one of 723 unique caste communities. The average community size is 148 firms, Appendix Figure A2 plots the distribution of the number of firms per caste. When considering the effect of caste on the intensive margin of trade below, we consider the sample of all 1,461,018 transactions recorded between these firms over our six year period, these transactions take place within 764,767 unique supplier-buyer pairs.

Given the size of our data, the universe of all potential supplier-buyer matches is extremely large (22 billion potential pairs) and computationally intractable. To consider the effect of castes on the extensive margin of trade we therefore define a ‘potential trade’ sample. We first define a client as a firm observed at least once on the purchasing side of a transaction, and a supplier as a firm observed at least once the selling side of a transaction - firms can be, and often are, both clients and suppliers. We then restrict the set of available suppliers for each client using information on the products sold by firms. For each client in our data observed trading with suppliers selling products $P$, we consider the set of all suppliers selling products $P$ and randomly include 25% of them as ‘potential suppliers’ for this client. This ‘potential trade’ sample contains 202 million potential pairs. We consider instead the full set of ‘potential suppliers’ for a single year as a robustness check. This sample definition essentially assumes that the set of products that firms trade is fixed, and not affected by caste networks. To relax this assumption and allow, for example, for the possibility that firms adjust their input mix based on the caste of their potential suppliers, we consider a second, large potential

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trade sample based on ‘recipes’ in the spirit of Atalay et al. (2019) as a robustness check. To construct this sample, we consider as potential suppliers for each client selling products \( P' \) a random 25% of the set of all suppliers seen trading with any client selling products \( P' \).

Table 1 presents descriptive statistics for our transaction data. We see that firms have an average of 3 suppliers, but nearly 500 potential suppliers to choose from, of which 17 are from their own caste. There is substantial entry and exit in our data - we observe firms for an average of 3 to 4 years. The potential trade data, described in the last panel, shows that the trade matrix is very sparse: only 0.7% of the potential supplier-client pairs in our data are observed trading, and 3.6% of potential supplier-client pairs are from the same caste.

3 Empirical evidence on community networks and trade

3.1 Stylized facts

Graphical evidence. Figure 1 presents graphical evidence on the role of castes in firm-to-firm trade using our sample of potential trade. We plot the relationship between how much a firm is observed trading with others in the same caste and how much it could potentially trade with same-caste firms given the distribution of castes in the potential trade data. Panel a) plots the share of firms’ inputs purchases from same-caste suppliers as a function of the share of same-caste suppliers in all their potential suppliers (‘potential’ same-caste input share). Panel b) plots the share of firms’ sales sold to same-caste clients as a function of the share of same-caste clients in their potential clients (‘potential’ same-caste sales share). Potential clients and suppliers are as defined above, and weighted by their average network sales, so that these potential input and sale shares can be interpreted as how much firms would trade within their caste if they randomly chose their trading partners (Bernard et al., 2019, use a similar approach to consider how distance affects firm-to-firm transactions).³

We see that firms systematically trade a lot more within their caste than they would if trading relationships were randomly chosen: each point on both panels

³Our baseline potential trade sample allocates potential suppliers to each client and is used to produce panel a). To produce panel b) we allocate potential clients to each supplier using the same method.
is clearly above the 45 degree line. This is true both for firms in large castes (those with high potential same-caste shares) and for firms in smaller castes. On average, firms’ potential same-caste input and sale shares are both 3.6%, but the average observed same-caste input share is more than double the potential share, at 8.4%, and the average observed same-caste sale share is nearly four times higher, at 11.2%.

This graphical evidence is a first indication that castes affect firm-to-firm trade, but it could be confounded by firms in the same caste making similar location or product choices. In what follows we turn to a regression framework to quantify the effect of caste on both the intensive and extensive margin of trade whilst controlling flexibly for all determinants of trade that could be correlated within caste networks.

Regression evidence. To measure the effect of caste networks on trade we estimate the following gravity equation augmented to allow for destination (client $i$) and origin (supplier $j$) fixed effects that vary across years $t$:

$$
\ln(Y_{ijt}) = \beta \mathbb{1}(c_i = c_j) + \gamma X_{ijt} + \mu_{it} + \mu_{jt} + \epsilon_{ijt}
$$

where $Y_{ijt}$ is log sales from $j$ to $i$ in year $t$ when we consider the intensive margin of trade, and an indicator equal to 1 when we consider the extensive margin, $\mathbb{1}(c_i = c_j)$ is an indicator equal to 1 if the owners of firms $i$ and $j$ belong to the same caste, $\mu_{it}$ and $\mu_{jt}$ are, respectively, supplier and client fixed effects interacted with year fixed effects, and $X_{ijt}$ is a set of controls defined at the $ij$ pair and period $t$ level, discussed below. We use the potential trade sample defined above when considering the extensive margin, and the sample of all positive sales when considering the intensive margin. Standard errors are two-way clustered at the level of the client and the supplier.

Castes play an essential role in economic and social interactions so we could see firms trading more with others in their own caste (a positive $\beta$) even in the absence of caste playing a direct role in firm-to-firm trade for. First, castes are known to affect occupational choice (Cassan et al., 2021) so firm owners of the same caste may find themselves in the same supply chains because of their sector choice. To control for this channel we include fixed effects for the interaction of both firms’ products. Second, some castes are concentrated geographically, so firm owners
may choose to trade more with others in their caste simply because of lower transport costs. We control for this channel by controlling non-parametrically for the effect of distance on trade by including fixed effects for the interaction of the location (postcode) in which both firms are located (Head and Mayer, 2014). Third, firm owners in the same caste may face similar aggregate shocks: the role of castes as providers of credit and insurance implies that unobserved shocks to firm owners in the same caste are likely to be correlated. Allowing for arbitrary shocks over time to both clients and suppliers ensures that our estimates of $\beta$ cannot be driven by such caste-level shocks.

Table 2 presents our results on the effect of castes on the extensive margin of trade, obtained by running specification (1) on the potential trade sample. Coefficients are rescaled by the average probability that two firms trade in our potential trade sample, so they can be interpreted as the effect of caste on the probability that two firms choose to trade. We see that being in the same caste increases the probability that two firms trade by 130% in the specification with no controls (column 1). Adding interactions for the location of the client and the supplier (in column 2), firm × year fixed effects (in column 3) and interactions for the products sold by the client and the supplier (in column 4) all decrease the effect of two firm owners being of the same caste on the probability that they trade, as expected. Our preferred estimate, in column (4) indicates that being of the same caste doubles the probability that two firms trade.

Estimates of the effect of castes on the intensive margin of trade in Table 3 are obtained by running specification (1) on the sample of all positive trades. We see again that controlling for firms’ joint locations, products sold, and (in particular) allowing for arbitrary shocks to clients or suppliers decreases the effect of castes on trade, but our preferred estimate in column 4 indicates that firm owners in the same caste trade substantially more with each other, by close to 19%. Overall, results in Tables 2 and 3 indicate that castes substantially increase both the probability that two firms trade and, when they do, how much they trade, even when controlling non-parametrically for other firm choices (location, products) that are likely correlated within castes and allowing for arbitrary caste-level shocks.

Tables A1 and A2 consider the robustness of our estimates of the effect of
castes on trade to our data construction, sample and specification choices. In columns 1 to 7 we exclude firms whose products are not defined at the detailed 4-digit level, consider several alternative assignments of last name to castes, exclude the largest 3 castes and all firms with no same-caste potential partner, and consider standard errors clustered two-way at the level of the client’s industry and location. Results are remarkably similar across specifications and samples. For the extensive margin results we consider alternative ways to define firms’ potential trading partners, looking at one year (2013) only to keep manageable sample sizes. We find that keeping all potential trading partners (instead of a random 25% sample) does not affect our results. When using the ‘recipes’ potential trading partners definition in the spirit of Atalay et al. (2019), defined above, we no longer constrain a firm’s potential suppliers to sell products this firm is observed buying. Our estimate of the effect of castes in this sample could therefore also captures the fact that firms’ caste networks may also affect which inputs they buy. We find a larger estimate using this sample than with our baseline sample, suggesting this may be the case. Finally, Table A4 tests whether the caste effects we observe reflect the role of jati networks or simply a preference for trading within the larger caste varna groups (there are four varna groups, with an additional dalit group so we allocate each firm to one of five large groups). We find a small effect of varnas on trade of roughly 7% the magnitude of our baseline caste effect, which remains unchanged when we control for varnas.

3.2 Mechanisms

Having established a large effect of caste on the extensive and intensive margin of firm-to-firm trade, we now turn to discussing potential mechanisms which could explain why firms trade more within than across castes.

Contractual frictions. A large literature on client-supplier relationships in developing countries argues that contractual frictions loom large in this context (see Macchiavello, 2022, for a review), and that social networks can help alleviate these frictions by relying on informal information and sanction mechanisms (Greif, 1993, 2006). Given their importance in the organization of Indian society, caste networks could enable relational contracts to emerge, allowing for trading relationships to be sustained even in India’s notoriously weak contract enforcement
environment (Boehm and Oberfield, 2020). We test this hypothesis in two ways. We first consider whether the effect of caste on trade varies for inputs that are more relationship-specific, using the classification from Rauch (1999) to attribute a relationship-specificity score to the products sold by the supplier, as explained above. Hold-up problems are more likely to arise with relationship-specific goods (Iyer and Schoar, 2015); if castes networks sustain informal enforcement mechanisms, we expect castes to increase trade in these products more than trade in homogeneous products. Second, we follow Boehm and Oberfield (2020) and use court congestion at the district level to proxy for the strength of formal enforcement mechanisms. If castes help enforce contracts, the caste effect on trade should be higher in areas in which formal enforcement channels are weaker.

Table 4 shows evidence consistent with caste networks alleviating contractual frictions. We see that the effect of caste on trade is higher in areas with more congested courts and for relationship specific products, for both the intensive and extensive margins of trade. A one standard-deviation increase in court congestion (in the traded product’s relationship specificity score) increases the intensive margin caste effect by 1.4 (2.4) percentage points and the extensive margin effect by 10.4 (9.6) percentage points. The coefficients for the same caste indicator in the last two columns can be interpreted as the effect of castes for trade that occurs in contexts with low (or no) contractual frictions: trade of perfectly homogeneous products in areas in which courts complete all cases within two years of them being filed. We see that the effect of castes on such trade, whilst much lower than the average effect, is still economically and statistically significant at roughly one-third of the average effect on both the extensive and intensive margins.

**Taste-based discrimination.** We test for the existence of taste-based discrimination by looking at the effect of a firm’s caste preference on its survival probability in later years. This test is inspired by Weber and Zulehner (2014) who build on the argument in Becker (1957) that firms with strong discriminatory prefer-

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4 Firms that exit our data may not necessarily stop operating - they may merely have chosen to stop paying VAT to the state government. Whilst informal firms are common in India, it is relatively easy for the tax authorities to find firms, and make them pay their taxes, if they were registered with the tax authorities in the previous year. Firms below a certain size do not have to pay VAT, they are still required to file taxes but their not doing so may be tolerated by the authorities. Overall, an exit from our data can be interpreted as either a sign that the firm stops operating, or that it becomes so small it thinks the tax authorities will ignore the fact that it has stopped filing taxes. In both cases, an exit is a sign of poor profitability.
ences will forego profits by submitting to these preferences and, in competitive markets, will eventually be forced out. In our context, this implies that firms with strong own-caste preferences (proxied for by an own-caste input share above industry average) will be less likely to survive. Specifically, we model the discrete hazard function \( h(t|p, D) \) as the probability that firm \( i \) exits in year \( t \) given that it existed up to year \( t - 1 \), as a function of the strength of its own-caste preference \( p \), measured by its share of own-caste inputs relative to the industry average, where the hazard rate is allowed to vary by each interaction of a firm’s district and industry and we control flexibly by firm size.

Results on firm survival as a function of their caste preference are presented in Table 5. We see that firms with strong preferences for trading within their caste are more likely to exit. A one standard deviation increase in a firm’s own-caste share (relative to the industry average) is associated with a 2.3% higher risk of exit in every time period. This evidence is consistent with part of the observed effect of castes on trade being explained by firms being prejudiced against trading outside of their caste networks.

**Statistical discrimination.** Finally, we note that statistical discrimination, whereby firms are reluctant to trade with others belonging to a group with worse outcomes in expectation, is unlikely to explain the patterns we observe. This is because our caste effects reflect symmetric preferences for in-group interaction, not asymmetric preferences with most firms preferring to avoid a specific group with worse outcomes. Inaccurate statistical discrimination, as defined by Bohren et al. (2019a), could however play a role: firms could hold biased beliefs about those outside their caste. They could incorrectly expect them to be worse-performing trading partners by for example providing worse-quality goods compared to trading partners from their own caste. Bohren et al. (2019b) show that looking at the dynamic patterns of discrimination helps uncover biased beliefs, because individuals holding biased beliefs about others’ potential performance will change these beliefs as more performance is observed. Building on their intuition, we consider how the caste effect on trade changes over time, as firms in a trade relationship learn about each other’s suitability as trading partners. If firms systematically and incorrectly believe that partners from their own caste are better performers (relative to partners from other castes) than they truly are, we should see within-caste relationships fail to thrive relative to across caste relationships. This would in turn
lead to the effects of caste on trade in Tables 2 and 3 to diminish in pairs that have been trading longer.

Figure 2 uses the panel dimension of our data to investigate whether the effect of caste on trade fades over time. Looking at a sample of newly formed pairs we find that this effect is remarkably stable over the 5 years we can observed them for. In panel a) we see that, if anything, same-caste pairs are slightly more likely to survive - the opposite of what we would expect if firms were de-biasing their incorrect beliefs over time. The intensive margin effect of caste on trade in panel b) is fairly stable over time, with firms buying 12-25% more from same-caste suppliers regardless of how long the trading relationship has been in existence. Overall, we see no evidence of the effect of caste on trade decreasing as firms learn more about each other. This suggests inaccurate statistical discrimination isn’t driving our results. Consistent with this, in Table A3 we find no evidence that caste networks affect trade less when either the client or the supplier has more experience (proxied for by time since registration).

Overall, our results indicate large effects of caste networks on trade at the intensive and extensive margin. We find evidence consistent both with castes alleviating market frictions, and with part of the caste effect being driven by taste-based discrimination. Our next section builds a model of firm-to-firm transactions to enable us to quantify the overall effect of castes on trade.

4 A model of firm-to-firm networks with communities

We use a theoretical framework of buyer-supplier networks with two-sided firm heterogeneity and endogenous match formation, built on Bernard et al. (2022). Our application of the Bernard et al. (2022) framework to the context of West Bengal, India, is motivated by the following patterns in our firm-to-firm data.

Fact 1: The distributions of firm sales and seller-customer links are highly dispersed

Figure 3 plots the distribution of firm size (total sales to the network), links with customers and links with suppliers demeaned at the 4-digit ISIC industry. The distributions are highly dispersed, expanding over several orders of magnitude. Firms on either side of the distribution have 100 times larger or lower sales than the industry mean, with some firms in the right tail of the distribution having
sales 20,000 larger than the industry mean. The high dispersion also appears in
the number of sellers and buyers, with some firms having 30 to 50 times more
connections than the industry mean. This high dispersion in the sales and links
distribution suggests that firm heterogeneity is high in West Bengal, justifying a
model with firm-heterogeneity.

**Fact 2: Firms with more customers have higher sales and higher sales per customer** In
Figure 4 we plot network sales over the number of customers (panel a) and the
network sales per customer over the number of customers (panel b). The pattern
is clear: large firms have more clients and also higher sales per client. This
pattern suggests that firm size shapes the ability to adopt more clients, and to
sell more to those clients. The positive correlation between size and the number
of clients suggests a strong connection between firm-heterogeneity, firm size and
firm connections.\(^5\)

**Fact 3: Sellers with more customers match with customers who have fewer suppliers on
average.** Figure 5 shows a binned scatterplot of the average number of suppliers
to firm i’s customers on the y-axis against the number of i’s customers, on a log-
log scale. We can see a clear negative slope: firms with less customers match with
very well connected customers, while firms with many customers match with
less-well connected firms on average. This pattern is known as negative degree
assortativity and is a well-known feature of business-to-business networks. This
patterns motivates the choice of a parsimonious model of firm-matching in which
a match is form when the profits of the match are larger than the cost of the match.
In this class of models, small firms are only able to match to large partners while
large firms match, on average, with less well connected, smaller suppliers. In the
remaining part of this section, we develop a firm-to-firm model that is consistent
with these data patterns and will also feature firm community-affiliation.

\(^5\)Bernard et al. (2022) find a negative correlation between network sales per customer and
number of customers, suggesting that firms with many customers are not able to sell more to each
customer, which implies a negative correlation between productivity and matching ability. Our
data pattern coincides with patterns uncovered in Norwegian data in ()
4.1 Theoretical framework

We first present the model conditional on a fixed firm network, and subsequently introduce a parsimonious firm-to-firm matching model.

There are three sources of firm heterogeneity. First, firms have different productivity levels, that help them produce inputs more efficiently. Second, firms have different relationship capabilities, that allow them to create new firm-to-firm relationships by paying different fixed costs. Finally, firms belong to a specific caste community. We specify how castes affect trade in the following subsection.

4.1.1 Technology and Demand

The economy is formed by a unit continuum of firms, each with the following production function:

\[ y(i, g) = \kappa z(i)l(i)^{\alpha}v(i)^{1-\alpha}, \]

where \( y(i) \) is the quantity of output produced by firm \( i \), \( z(i) \) is the productivity, \( l(i) \) is the amount of labor used by firm \( i \), \( \alpha \) is the labor share, and \( \kappa \geq 0 \) is a normalization constant.\(^6\) \( v(i) \) is the bundle of intermediate inputs used by the firm in production, given by:

\[ v(i) = \left( \int_{S(i)} v(k, i) \frac{(\sigma-1)}{\sigma} dk \right)^{\sigma/(\sigma-1)}, \]

where \( v(k, i) \) is the quantity that firm \( i \) purchases from firm \( k \), \( S(i) \) is the set of suppliers available to firm \( i \), and \( \sigma > 1 \) is the elasticity of substitution across suppliers within the sector. The input price index associated with the CES input demand function is given by \( P(i) = \left( \int_{S(i)} p(k)^{1-\sigma} dk \right)^{1/(1-\sigma)} \), where \( p(k) \) is the price charged by supplier \( k \). This input price index will be lower when firm \( i \) is able to match with efficient suppliers (that charge a low price \( p(k) \) for their inputs) and when firm \( i \) can source from a larger set of suppliers (thanks to the properties of the CES input bundle aggregator).

Following Bernard et al, we choose the wage as the numeraire (\( w = 1 \)), the

\[^6\kappa = \alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}\]
marginal cost of firm $i$ selling to firm $j$ is:

$$c(i, j) = \frac{P(i)^{1-\alpha}}{z(i)\delta_z^{1-C_{i,j}^*}}$$  \hspace{1cm} (4)

where $C_{i,j} = 0$ if the firms belong to the same caste, 1 otherwise. Parameter $\delta_z^{1-C_{i,j}}$ is the efficiency effect of same-caste trading. As we can see, both the firm’s productivity and the firm’s supplier connexions help reduce the marginal cost of production.

**Final demand** Final consumers have a CES utility function with the same elasticity of substitution $\sigma$ across output varieties. We assume that the representative consumer is the shareholder of all firms, so that aggregate profits $\Pi$ become part of consumer income. Aggregate income $X$ is therefore the sum of aggregate labor income and aggregate corporate profits, $X = wL + \Pi$ where $L$ is inelastically supplied labor.

**4.1.2 Firm-to-Firm Sales**

Each firm faces demand from other firms, as well as from final consumers.\(^7\) Given our assumption about the production function and the demand for intermediates, we can solve for the sales from firm $i$ to firm $j$:

$$m(i, j) = p(i, j)^{1-\sigma}P(j)^{\sigma-1}M(j),$$  \hspace{1cm} (5)

where $p(i, j) = \mu c(i, j)$.

$$m(i, j) = p(i)^{1-\sigma}P(j)^{\sigma-1}M(j),$$  \hspace{1cm} (6)

where $M(j)$ are total intermediate purchases by firm $j$, $\int_{S(j)} m(i, j)di$.

The market structure of monopolistic competition means that firms will choose to charge a constant mark-up over marginal costs, $p(i, j) = \mu c(i, j)$, where $\mu = \ldots$
\( \sigma / (\sigma - 1) \). After rearranging, sales from \( i \) to \( j \) can be expressed as:

\[
m(i, j) = \left[ \frac{z(i) \delta_{z}^{1-C_{i,j}}}{\mu p(i)^{1-\alpha}} P(j) \right]^{\sigma-1} M(j)
\]  

(7)

Taking logs, it is easy to see that the model delivers a similar log-linear expression of firm-to-firm sales as the one we used in our empirical section. The caste dummy will identify the efficiency effect of intra-community trading.

### 4.1.3 Equilibrium Conditional on Network

The equilibrium can be computed in two separable steps. First, we describe the equilibrium given a fixed firm-to-firm network. Then, we solve for the equilibrium network introducing endogenous match formation.

A firm \( i \) is characterized by the tuple \( \lambda = (z; F) \), where \( z \) is productivity and \( F \) is a relationship fixed cost, in units of labor. \( z \) and \( F \) are potentially correlated, and \( dG(\lambda) \) denotes the (multivariate) density of \( \lambda \). We define the link function \( l(\lambda, \lambda') \) as the share of seller-buyer pairs \( (\lambda, \lambda') \) that match in a trade relationship.

**Backward fixed point.** For a given network structure, the equilibrium can be found by solving for two fixed points sequentially. Using the pricing rule \( p(\lambda, \lambda') = \mu c(\lambda, lambda') \) and the equation for marginal costs (3), the input price index can be solved by iterating on a backward fixed point problem:

\[
P(\lambda)^{1-\sigma} = \mu^{1-\sigma} \int P(\lambda')(1-\sigma)(1-\alpha) \left( z(\lambda') \delta_{z}^{1-C(\lambda,\lambda')} \right)^{\sigma-1} l(\lambda', \lambda) dG(\lambda')
\]  

(8)

The input cost index of firm \( \lambda = \mu^{1-\sigma} \int P(\lambda)(1-\sigma)(1-\alpha) z(\lambda)^{\sigma-1} dG(\lambda) \). Also note that total input purchases are \( M(\lambda) = \mu^{1-\sigma} \int P(\lambda)(1-\sigma)(1-\alpha) z(\lambda)^{\sigma-1} dG(\lambda) \).
Sales of a type-\(\lambda\) firm depend on final demand, \(X\), the productivity and input price index of the firm itself, \(z(\lambda)\) and \(P(\lambda)\), and the sales and input prices of its customers, \(S(\lambda')\) and \(P(\lambda')\). In addition, the sales of each seller will be affected by whether the seller and the buyer have the same caste affiliation. The equilibrium exists and is unique (Bernard et al. 2022).

### 4.1.4 Firm-to-Firm Matching

We now consider the general equilibrium when the firm-to-firm network is endogenous and sellers match with buyers if and only if the profits from doing so are positive. The seller incurs a relationship fixed cost \(F\varepsilon\) for every buyer it chooses to sell to, where \(F\) varies across sellers, and \(\varepsilon\) is an idiosyncratic shock that varies across seller-buyer pairs.\(^8\) In addition, creating the cost of creating a firm to firm link differs when both firms belong to the same Caste, so that the cost of creating a trade relationship is \(F\varepsilon\delta_F^{(1-C_{i,j})}\), where \(C_{i,j} = 0\) if caste(i)=caste(j), 1 otherwise.

Given this assumptions on the matching technology, the share of seller-buyer pairs \((\lambda, \lambda')\) that match and trade with each other is:

\[
l(\lambda, \lambda') = \int 1 [\ln \varepsilon < \ln \pi - \ln F + (1 - C_{i,j})\delta_F] \, dH(\varepsilon),
\]

where \([\cdot]\) is the indicator function, \(dH(\varepsilon)\) denotes the density of \(\varepsilon\), and the gross profits from the potential match are:

\[
\pi(\lambda, \lambda') = \frac{m(\lambda, \lambda')}{\sigma}.
\]

Notice that this expression will give us the trade probability for a pair type \((\lambda, \lambda')\). This trade probability depends on the profitability of the match and on

\(^8\)The introduction of this pair-specific shock is needed to smooth the problem and ensure that the matching function is continuous in the parameters of the model (Bernard et al. 2022).
the matching costs. It is worth highlighting that both caste parameters enter this equation and affect trade probabilities. The caste efficiency term \( \delta_z \), increases the match probability. The caste matching cost \( \delta_F \) affects the total matching costs. This expression shows why both caste effects could be driving the higher intra-caste trade probability.

This link function is also a fixed point problem, given the gross profits, the matching costs and the pair-shocks.

We can now explain how to solve for the general equilibrium, that nests the three fixed point problems. The algorithm is proposed by Bernard et al (2022): (i) Start from a guess for the link matrix, (ii) use equations (7) and (8) to solve for for \( P\Lambda \) and \( S(\lambda) \) sequentially. (iii) Calculate gross profits for all potential matches and compute the share of seller-buyer pairs that match according to equation (9). (iv) Go back to step (ii) and iterate until the link matrix converges.

4.1.5 Predictions on communities and trade in the model

The model delivers both an intensive margin equation (6) and an extensive margin equation (9) that we can compare to our reduced-form evidence.

1. Firm-to-firm sales are higher intra-caste

\[
\ln \left( m(\lambda, \lambda') \right) = (1 - C(\lambda, \lambda'))(\sigma - 1)\ln(\delta_z) + (\sigma - 1)\ln \left[ \frac{z(\lambda)}{\mu P(\lambda)^{1-\alpha}} \right] + \ln \left[ \frac{M(\lambda')}{P(\lambda')^{1-\sigma}} \right]
\]

(12)

Conditional on buyer and seller fixed effects, a positive coefficient on the caste-dummy is evidence of an efficiency effect of intra-caste trade \( \delta_z > 1 \).

2. Firm-to-firm trading probabilities are higher intra-caste

\[
\ell(\lambda, \lambda') = \int [\ln \epsilon < \ln \left( \frac{m(\lambda, \lambda')}{\sigma} \right) - \ln F + (1 - C(\lambda, \lambda'))\delta_F] dH(\epsilon),
\]

(13)
A higher trading probability within-caste could be evidence of both an efficiency
effect from same-caste trading ($\delta_z > 1$) and a lower matching cost for same-caste
pairs ($\delta_F < 0$)

5 Estimation and Results

We estimate the model using Simulated Method of Moments (SMM). We use the
following assumptions on the parameters. First, productivity $z$ and matching
ability $F$ are uncorrelated and log-normal. Second, we normalize the mean of
the productivity distribution to zero so that $\mu_z=0$. We are left then with five pa-
rameters to estimate: $\Gamma = \{\mu_{lnF}, \sigma_F, \sigma_z, \delta_z, \delta_F\}$. In addition, we have the following
parameters that we calibrate externally: $\{\sigma, \alpha, X, \sigma_\epsilon, \text{community links } C\}$, follow-
ing the literature. Further details are provided in the Appendix. To estimate our
due model parameters, we use six targeted moments: Mean(In clients), Var(In
clients),Var(In Sales), and our reduced form estimates of the caste effect on the
intensive and the extensive margin of trade.

The first three moments follow from Bernard et al (2022), while the remaining
three help us identify our caste-parameters. The structure of the model enables
us to disentangle the efficiency and matching caste parameters that are consistent
with the firm distribution moments as well as with the reduced-form evidence.
Following the standard approach, our SMM estimates for $\Gamma$ solve:

$$\arg \min_{\Gamma} (x - x^s(\Gamma))^t(x - x^s(\Gamma)),$$

where $x$ are empirical moments and $x^s(\Gamma)$ simulated moments.

6 Model Estimation and Counterfactuals

6.1 Model estimation results

Table 6 reports the results from the SMM estimation. Column 1 reports the value
of the targeted moments in the data. Column 2 reports our estimated parameters
and value of the simulated moments. We find that the variance of the match-
ing ability is much higher than the variance of productivity, in line with recent
evidence on the importance of the firm network for firm outcomes. Crucially,
our estimates indicate that communities play a role in both the profitability of the match and the likelihood of the match. We find that $\delta_z = 1.068$, meaning that trade within-caste is 7% more efficient than trade across-caste. We find that $\delta_F = -2.7156$, implying that matching costs within-caste are $\exp(-2.71)=15$ times lower than across-caste. Therefore, our estimation suggests a dual role for communities in firm-to-firm networks. Our estimated parameters provide a very good model fit, as all targeted moments are well matched. Columns 3 and 4 estimate alternative models in which we restrict communities by having an effect through only one margin. As we can see from the targeted moments, both models have problems to explain the caste-specific moments that we see in the data. This provides further evidence on our finding that communities affect trading efficiency as well as matching costs.

6.2 Counterfactuals

In this section, we use our estimated model to investigate how communities shape aggregate outcomes such as firm size, firm connections and welfare. We perform two counterfactuals. In the first counterfactual, we ask: What would be the aggregate implications of allowing all firm-pairs to benefit from the higher efficiency and the lower matching costs that firms in the same communities can use? To find out, we perform counterfactual 1: all firm-pairs enjoy the benefits of within-caste trade: higher trading efficiency and lower matching costs. In the second counterfactual, we ask the opposite questions: What would be the aggregate implications of eliminating the advantages of trading within-communities? To investigate this, we run counterfactual 2: no firms-pairs benefit from the within-caste higher efficiency and lower matching costs.

Table 7 reports the results for both counterfactuals. The outcomes are reported as a share of the baseline model, estimated in the previous section. What is the aggregate effect of allowing all firms to “participate” in the same community? We find that expanding community-affiliation to all firms has very large aggregate effects. Welfare in the economy goes up by 93%. This comes from an 87% increase in total firm-to-firm connections, and an input price reduction of almost 20%. As a result of the increased trading efficiency and the lower matching costs, average firm size (network sales) grows by 34%. The reason for this large effect is that
only 3% of the potential firm-pairs in our data are same-caste pairs. Thus, by making all firms part of the same community, we increasing the trading efficiency and the matching ability for 97% of the sample. In Appendix Table ??, we provide the counterfactual effects of each of the two margins of the caste-effect (intensive and extensive margins). We find that most of the effect comes from the reduction in the matching cost for same-caste pairs. Our results point to an important role of community networks for firm-to-firm trade and aggregate outcomes.

On the other hand, eliminating community networks has more moderate effects. This is due to the small number of same-caste pairs in the data. If we eliminate the advantages in efficiency and matching ability estimated for same-caste pairs, we find that welfare falls by 3.7% and total network connections by 2.4%, while input price and firm size almost don’t change. Indeed, average network sales increases by 1.3%, due to the destruction of low-profitable, same-caste pairs that comes from the increase in the matching costs for same-caste pairs.

6.3 Distributional effects

Finally, we investigate the distributional implications of our two counterfactuals for firm size, number of connections. Our first object of interest is the firm network. Figure 6 plots the distribution of the trade probability (number of clients normalised by number of firms) in the three different scenarios: baseline, all firms in the same caste (one caste) and no caste groups (No caste). Relative to the baseline, the distribution of the number of clients from scenario 2, in which all firms belong to the same community, is shifted to the right, with a significant drop in the number of firms with very few connections, and a higher density in all other bins. This patterns shows how expanding the community-trading benefits to all firm-pairs would all firms gain more clients.

The second outcome of interest in the firm size distribution. There is a wide literature highlighting the lack of middle-sized and large firms in the data in LMICs. Our second counterfactual illustrates the crucial role that firm-to-firm networks could plan in increasing firm size. As we can see in figure 7, the firm size distribution shifts to the right when we allow all firms to trade as if they were affiliated within the same community. Eliminating caste networks does not affect the firm-size distribution.
Finally, we look at the distributional impact of allowing all firms to belong to the same community (counterfactual 2). Figure 8 plots the change in firm sales for each firm after they are all integrated into the same community, plotted against the firm size (total sales) at baseline. The figure shows that sales increase for almost all firms, except for the very large ones. In particular, the smallest firms at baseline gain the most sales, more than doubling their sales. We can see that, on average, firms in the largest caste groups (that were benefitting the most from the intra-caste higher efficiency and matching ability), see the smallest increases in sales. These counterfactuals point to potentially large effects of improving firm-to-firm networks for development outcomes such as firm size and welfare. Using our model estimates, we find large aggregate effects of intra-community trading, if these benefits could be enjoyed by all firms. Future work should be directed at understanding better precisely why communities facilitate trade, in order to design policies that could provide the benefits highlighted by our counterfactuals.

7 Conclusion

This paper has considered the role of community (caste) networks in shaping firm-to-firm trade in India. Using panel data on firm-to-firm transactions and information on the firm owner’s community, we find that two firms are twice as likely to trade, and when they do trade, trade 20% more, when they belong to the same community. We provide evidence consistent both with communities alleviating frictions and with taste-based discrimination.

To understand the aggregate effects of communities on the economy via trade, we build a model of network formation in which communities affect both the productivity of a client-supplier relationship and the cost of forming the relationship. Estimating model parameters using our reduced-form evidence, we find that removing all inter-caste trading frictions would nearly double the number of trading relationships, and lead to firm growth, particularly amongst smaller firms.
References


BECKER, G. S. (1957): *The economics of discrimination*, University of Chicago press.


the Oxford Handbook of Caste in Contemporary/Modern Times, Surinder S. Jodhka and Jules Naudet (editors).


The graphs illustrate the relationship between potential same-caste trade and observed same-caste trade, averaged within 20 vintiles of potential own-caste trade share. Potential same-caste trade (input or sales) share is the average share of same-caste trading partners in a firm’s all potential trading partners, where each partner is weighted by its average network sales. Panel a) plots firms’ observed input share purchased from same-caste suppliers as a function of their potential same-caste input share. Panel b) plots firms’ observed sales share sold to same-caste clients as a function of their potential same-caste sales share. Each firm is weighted by its average annual network trades, we exclude the 5 largest firms.
These graphs plot the trade dynamics for newly formed trade relationships separately for same-caste relationships and all other relationships. Each point represents a predicted outcome, computed separately for pairs for which both firm owners belong to the same caste and for other pairs, with 95% confidence intervals. Our sample is the sample of firm pairs that trade in the second year in our data (2011-12) but not in the previous year, and for which both the supplier and the seller are present in the data in all subsequent year. Estimates of the effect of the two firms being in the same caste on trade over time are obtained by using an augmented version of our specification 1 that allows the same caste effect to vary in each year: 

$$Y_{ijt} = \sum \beta^1 (c_i = c_j) \times 1 (Year_{trade} = k) + \sum_{k=1}^{5} \theta^1 (Year_{trade} = k) + \gamma X_{ijt} + \mu_i + \mu_j + \epsilon_{ijt}.$$ 

In panel (a), $Y_{ijt}$ is an indicator equal to 1 if firm pair $ij$ trades in year $t$; in panel (b), $Y_{ijt}$ is the log of observed trade between $i$ and $j$ in year $t$. We control throughout for supplier and client fixed effects, firms’ joint locations and products sold, following the specification used in column (4) of Tables 2 and 3. Indicated confidence intervals at the 95% level, standard errors are clustered two-way at the supplier and client levels. Sample size: (a) $N=485,324$ (b) $N=226,709$. 

---

**Figure 2: Predicted trade, new pairs 2011-2012**

(a) Predicted trade probability

(b) Predicted trade volume (conditional)
Figure 3: Distribution of firm sales, number of customers and number of suppliers.

Note: The graph illustrates the density of network sales, total customers and total suppliers in the firms in our dataset.
Figure 4: Total Network Sales, Average Sales and Number of Customers

Note: The binned scatterplots group firms into 20 equal-sized bins by number of customers (log), and compute the mean of the variables on the x- and y-axes in each bin. Network sales are firm’s total sales to customers in the domestic production network. All variables are demeaned by 4-digit industry averages. The upper panel plots networks sales over total number of customers while the lower panel plots average sales per customer over total number of customers.
Figure 5: Degree Assortativity

Note: The binned scatterplot groups firms into 20 equal-sized bins by number of customers (log), and computes the mean of the variables on the x and y-axes in each bin. Average number of suppliers refers to the geometric mean of the number of suppliers serving the customers of firm i. All variables are demeaned by 4-digit industry averages.
Figure 6: Distribution of the number of network links

Note: The figure plots the distribution of the total number of clients per firm in the estimated model (baseline) and in two counterfactual scenarios. Counterfactual 1 (All caste) assumes all firm-pairs can benefit from the advantage in caste efficiency and caste matching cost. Counterfactual 2 (No caste) assumes that there are no communities in the economy, so no firms can benefit from the higher efficiency or matching ability within-caste.
Figure 7: Firm size distribution

Note: The figure plots the distribution of (log) firm size in the estimated model (baseline) and in two counterfactual scenarios. Counterfactual 1 (C1: one caste) assumes all firm-pairs can benefit from the advantage in caste efficiency and caste matching cost. Counterfactual 2 (C2: no caste) assumes that there are no communities in the economy, so no firms can benefit from the higher efficiency or matching ability within-caste.
Figure 8: Change in sales and firm size

Note: The binned scatterplots group firms into 20 equal-sized bins by firm size (log), and compute the mean of the variables on the x- and y-axes in each bin. Change in network sales is network sales under counterfactual 1 divided by network sales in the baseline model. Counterfactual 1 (C1: one caste) assumes all firm-pairs can benefit from the advantage in caste efficiency and caste matching cost.
Table 1: Sample descriptives

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A: Firms</strong></td>
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<tr>
<td>Turnover (1000 INR)</td>
<td>23.52</td>
<td>30.90</td>
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<td>Trading partners</td>
<td>3.28</td>
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<td>Years active</td>
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<td>1.93</td>
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</tr>
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<td><strong>B: Potential trade</strong></td>
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<tr>
<td>Trade probability (%)</td>
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<td>8.46</td>
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<td>Transaction amount (1000 INR)</td>
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<td>279.38</td>
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<tr>
<td>Same caste probability (%)</td>
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<tr>
<td>Observations</td>
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This table presents annual averages, the potential trade data is constructed as described in the text. Transaction amount in panel C is conditional on observed trade.
Table 2: Caste effect on the extensive margin of trade

<table>
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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<tr>
<td></td>
<td>(1(\text{Trade}))</td>
<td>(1(\text{Trade}))</td>
<td>(1(\text{Trade}))</td>
<td>(1(\text{Trade}))</td>
</tr>
<tr>
<td>Same caste (rescaled)</td>
<td>1.312 (*)</td>
<td>1.003 (*)</td>
<td>1.000 (*)</td>
<td>0.991 (*)</td>
</tr>
<tr>
<td>SE</td>
<td>(0.029)</td>
<td>(0.026)</td>
<td>(0.021)</td>
<td>(0.021)</td>
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<tr>
<td>Client location X Seller location FE</td>
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<td>X</td>
<td>X</td>
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<td>X</td>
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<tr>
<td>Seller X Year FE</td>
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<td>Client Industry X Seller Industry FE</td>
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<td>202,496</td>
<td>202,496</td>
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</table>

This table presents results obtained from running specification (1), described in the text. The variable ‘same caste’ is an indicator equal to 1 divided by the mean probability of trade in the sample (.00726) if the two firms are in the same caste, 0 otherwise, so that coefficients can be read as the effect of caste on the probability that two firms trade. All columns from column 2 onwards include fixed effects for each interaction of the location (postcode) of the seller and the location (postcode) of the client, columns (3) and (4) include supplier × year and client × year fixed effects and column (4) includes fixed effects for each interaction of the product sold by the seller and the product sold by the client. Standard errors clustered two-way at the level of the supplier and the client in parentheses. Significance levels: \(^* p<0.1\); \(^{**} p<0.05\); \(^{***} p<0.01\).
Table 3: Caste effect on the intensive margin of trade

<table>
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<tr>
<th></th>
<th>(1) Log. trade</th>
<th>(2) Log. trade</th>
<th>(3) Log. trade</th>
<th>(4) Log. trade</th>
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<td>0.332***</td>
<td>0.198***</td>
<td>0.188***</td>
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<td></td>
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<td>(0.012)</td>
<td>(0.009)</td>
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<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Seller location FE</td>
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<td></td>
<td></td>
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<tr>
<td>Client X Year FE</td>
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<td>X</td>
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<td>Seller X Year FE</td>
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<tr>
<td>Client Industry X</td>
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<td>X</td>
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<tr>
<td>X Seller Industry FE</td>
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<td>Obs. (thousand)</td>
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</tbody>
</table>

This table presents results obtained from running specification (1), described in the text. The variable ‘same caste’ is an indicator equal to 1 if the two firms are in the same caste, 0 otherwise. All columns from column 2 onwards include fixed effects for each interaction of the location (postcode) of the seller and the location (postcode) of the client, columns (3) and (4) include supplier × year and client × year fixed effects and column (4) includes fixed effects for each interaction of the product sold by the seller and the product sold by the client. Standard errors clustered two-way at the level of the supplier and the client in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.
Table 4: Caste and trade frictions

<table>
<thead>
<tr>
<th></th>
<th>(1) Log. trade</th>
<th>(2) Log. trade</th>
<th>(3) Log. trade</th>
<th>(4) Log. trade</th>
<th>(5) Log. trade</th>
<th>(6) Log. trade</th>
</tr>
</thead>
<tbody>
<tr>
<td>Same caste</td>
<td>0.616***</td>
<td>0.734***</td>
<td>0.354***</td>
<td>0.135***</td>
<td>0.121***</td>
<td>0.068***</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.068)</td>
<td>(0.080)</td>
<td>(0.025)</td>
<td>(0.021)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Same caste × Court</td>
<td>0.632***</td>
<td>0.636***</td>
<td>0.088**</td>
<td>0.087**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>cong.</td>
<td>(0.074)</td>
<td>(0.074)</td>
<td>(0.039)</td>
<td>(0.039)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same caste × Rel. spec.</td>
<td>0.403***</td>
<td>0.406***</td>
<td>0.104***</td>
<td>0.103***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.096)</td>
<td>(0.096)</td>
<td>(0.029)</td>
<td>(0.029)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This table presents results obtained from running specification (1) augmented with an interaction term. The variable ‘same caste’ is an indicator equal to 1 if the two firms are in the same caste, 0 otherwise. The variable court congestion is the share of filed cases which were decided cases after 2 years in the client’s district. The variable ‘relationship-specificity’ measures the share of goods in the seller’s NIC4 category that are not traded on central exchanges according to Rauch (1999). All columns include fixed effects for each interaction of the location (postcode) of the seller and the location (postcode) of the client, supplier × year and client × year fixed effects and fixed effects for each interaction of the product sold by the seller and the product sold by the client. Standard errors clustered two-way at the level of the supplier and the client in parentheses. Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01.
Table 5: Caste effect on firm exit

<table>
<thead>
<tr>
<th></th>
<th>(1) Exit</th>
<th>(2) Exit</th>
<th>(3) Exit</th>
<th>(4) Exit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Own caste share, demeaned (volume)</td>
<td>0.095*** (0.000)</td>
<td>0.091*** (0.000)</td>
<td>0.095*** (0.000)</td>
<td>0.096*** (0.000)</td>
</tr>
<tr>
<td>Firm age</td>
<td>-0.081*** (0.000)</td>
<td>-0.087*** (0.000)</td>
<td>-0.085*** (0.000)</td>
<td>-0.087*** (0.000)</td>
</tr>
<tr>
<td>Log turnover</td>
<td>-0.275*** (0.000)</td>
<td>-0.282*** (0.000)</td>
<td>-0.300*** (0.000)</td>
<td></td>
</tr>
</tbody>
</table>

Stratification     Post code  Industry & Post code  Industry & Post code & Size decile

Observations 364,967 364,967 364,967 364,967

This table presents the untransformed coefficients from our Cox model with subgroup-specific baseline hazards. Standard errors are clustered at the Post code X good level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.
Table 6: Estimation results: parameter estimates and model fit

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Baseline</th>
<th>No matching effect</th>
<th>No efficiency effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_{\ln F}$</td>
<td>13.5532</td>
<td>12.6192</td>
<td>13.5985</td>
<td></td>
</tr>
<tr>
<td>$\sigma_z$</td>
<td>0.0935</td>
<td>0.0005</td>
<td>0.0819</td>
<td></td>
</tr>
<tr>
<td>$\sigma_F$</td>
<td>4.5136</td>
<td>4.6539</td>
<td>4.5178</td>
<td></td>
</tr>
<tr>
<td>$\delta_z$ (caste efficiency)</td>
<td>1.0689</td>
<td>1.2893</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>$\delta_F$ (caste matching cost)</td>
<td>-2.7156</td>
<td>-</td>
<td>-2.9073</td>
<td></td>
</tr>
<tr>
<td><strong>Targeted moments</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Var(Sales)</td>
<td>2.38</td>
<td>2.4532</td>
<td>2.3834</td>
<td>2.4419</td>
</tr>
<tr>
<td>Var(In Clients)</td>
<td>2.20</td>
<td>2.1771</td>
<td>2.1678</td>
<td>2.1869</td>
</tr>
<tr>
<td>Mean(In Clients)</td>
<td>-4.55</td>
<td>-3.9724</td>
<td>-3.6755</td>
<td>-3.9724</td>
</tr>
<tr>
<td>RF coeff on Sales</td>
<td>0.19</td>
<td>0.1881</td>
<td>0.7542</td>
<td>-0.0061</td>
</tr>
<tr>
<td>RF coeff on Trade prob</td>
<td>1.00</td>
<td>1.2729</td>
<td>0.2907</td>
<td>1.2749</td>
</tr>
<tr>
<td>Mean(In Caste Clients)</td>
<td>-2.510</td>
<td>-2.9837</td>
<td>-3.4306</td>
<td>-2.9843</td>
</tr>
<tr>
<td><strong>Untargeted moments</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean(In Suppliers)</td>
<td>-4.8</td>
<td>-3.1679</td>
<td>-2.9016</td>
<td>-3.1669</td>
</tr>
<tr>
<td>Neg degree assortativity</td>
<td>-0.4673</td>
<td>-0.1793</td>
<td>-0.204</td>
<td>-0.1752</td>
</tr>
<tr>
<td>N clients and market sh.</td>
<td>0.01</td>
<td>0.0606</td>
<td>0.0643</td>
<td>0.0592</td>
</tr>
</tbody>
</table>
Table 7: Aggregate effects of Community networks: counterfactual exercises

<table>
<thead>
<tr>
<th>Outcome</th>
<th>C1: All in same caste</th>
<th>C2: No castes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Welfare change</td>
<td>1.9398</td>
<td>0.96325</td>
</tr>
<tr>
<td>Change in total number of connections</td>
<td>1.8787</td>
<td>0.97603</td>
</tr>
<tr>
<td>Change in average network sales</td>
<td>1.3498</td>
<td>1.0135</td>
</tr>
<tr>
<td>Change in average input price</td>
<td>0.83529</td>
<td>1.0092</td>
</tr>
</tbody>
</table>
Appendix
Figure A1: Sample entry from Singh (1996)

<table>
<thead>
<tr>
<th><strong>GARERI</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Synonyms:</strong> Bherihar, Pal [Bihar]</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>Groups/subgroups:</strong> Dhengar, Gangojoli, Nikhar, Phurukbadi [Bihar]</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>Subcastes:</strong> Dhengar, Farakhabadi, Gangajali, Nikhar [H.H. Risley]</td>
</tr>
<tr>
<td><strong>Titles:</strong> Kamblia, Kammali, Marar, Ratu [H.H. Risley]</td>
</tr>
<tr>
<td><strong>Surnames:</strong> Bhagat, Chowdhury, Mandal, Pal [Bihar]</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>Exogamous units/clans:</strong> Ahir, Bandharia, Chowharia, Khandel [West Bengal]</td>
</tr>
<tr>
<td><strong>Exogamous units/clans (gara):</strong> Ahir, Basdharia, Bilar, Chandel, Chaurasia, Nakwar [Bihar]</td>
</tr>
<tr>
<td><strong>Exogamous units/lineages:</strong> Ahir, Bandharia, Chowharia, Khandel [West Bengal]</td>
</tr>
</tbody>
</table>
Figure A2: Distribution of caste sizes

This graph plots the number of firms per caste.
Figure A3: Distribution of trade frictions

(a) Client’s court congestion, pair-level

(b) Seller’s good relationship-specificity, pair level
Figure A4: Firm survival and own-caste trade

The graph illustrates...
### Table A1: Robustness, Extensive margin

<table>
<thead>
<tr>
<th></th>
<th>2011 - 2016</th>
<th>2013</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (Trade)</td>
<td>(2) (Trade)</td>
</tr>
<tr>
<td>Same caste</td>
<td>0.991***</td>
<td>1.006***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Robustness</td>
<td>Main</td>
<td>4-digit NIC</td>
</tr>
<tr>
<td>Obs. (thousand)</td>
<td>202,496</td>
<td>116,756</td>
</tr>
</tbody>
</table>

Column (1) presents the results from our main specification as shown in Table 3. Column (2) restricts the sample to firms whose main good is defined at the 4-digit level. Column (3) uses the secondary caste, if available, to construct the 'Same caste' indicator. Column (4) restricts the sample to firms which have a name that explicitly connected to West Bengal in the original source. Column (5) excludes all firms from one of the 3 largest castes (Aguri, Baidya, Marwari). Column (6) excludes who have no potential trading partner from their own caste in the sample. Column (7) is based on the main sample, but uses two-way-clustered standard errors by Client location and industry. Columns (8) - (10) use only data from the year 2013: Column (8) uses the main sample described in the text. Column (9) uses the same procedure to identify potential sellers, but uses the full set of potential trading partners. Column (10) uses recipes to construct the set of potential suppliers as describe in the text, taking a 25% subset of potential trading partners. All columns include fixed effects for each interaction of the location (postcode) of the seller and the location (postcode) of the client, supplier × year and client × year fixed effects and fixed effects for each interaction of the product sold by the seller and the product sold by the client. If not indicated otherwise, standard errors clustered two-way at the level of the supplier and the client in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log. trade</td>
<td>Log. trade</td>
<td>Log. trade</td>
<td>Log. trade</td>
<td>Log. trade</td>
<td>Log. trade</td>
<td>Log. trade</td>
</tr>
<tr>
<td>Same caste</td>
<td>0.188***</td>
<td>0.198***</td>
<td>0.193***</td>
<td>0.147***</td>
<td>0.258***</td>
<td>0.184***</td>
<td>0.188***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.007)</td>
<td>(0.012)</td>
<td>(0.013)</td>
<td>(0.009)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Robustness</td>
<td>Main</td>
<td>4-digit NIC</td>
<td>2nd caste</td>
<td>West Bengali castes</td>
<td>No large castes</td>
<td>No small castes</td>
<td>Industry &amp; location clustered SEs</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Obs. (thousand)</td>
<td>1,461</td>
<td>885</td>
<td>1,461</td>
<td>620</td>
<td>866</td>
<td>1,196</td>
<td>1,461</td>
</tr>
</tbody>
</table>

Column (1) presents the results from our main specification as shown in Table 3. Column (2) restricts the sample to firms whose main good is defined at the 4-digit level. Column (3) uses the secondary caste, if available, to construct the ‘Same caste’ indicator. Column (4) restricts the sample to firms which have a name that explicitly connected to West Bengal in the original source. Column (5) excludes all firms from one of the 3 largest castes (Aguri, Baidya, Marwari). Column (6) excludes who have no potential trading partner from their own caste in the sample. Column (7) is based on the main sample, but uses two way-clustered standard errors by Client location and industry. All columns include fixed effects for each interaction of the location (postcode) of the seller and the location (postcode) of the client, supplier × year and client × year fixed effects and fixed effects for each interaction of the product sold by the seller and the product sold by the client. If not indicated otherwise, standard errors clustered two-way at the level of the supplier and the client in parentheses. Significance levels: ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01.
Table A3: Caste effect and firm age

<table>
<thead>
<tr>
<th></th>
<th>(1) (Trade)</th>
<th>(2) (Trade)</th>
<th>(3) (Trade)</th>
<th>(4) Log. trade</th>
<th>(5) Log. trade</th>
<th>(6) Log. trade</th>
</tr>
</thead>
<tbody>
<tr>
<td>Same caste</td>
<td>0.991***</td>
<td>0.979***</td>
<td>0.961***</td>
<td>0.188***</td>
<td>0.188***</td>
<td>0.189***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.021)</td>
<td>(0.022)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Experienced client</td>
<td>0.029</td>
<td></td>
<td></td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same caste ×</td>
<td></td>
<td>0.069**</td>
<td></td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experienced seller</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Obs. (thousand)</td>
<td>202,496</td>
<td>202,496</td>
<td>202,496</td>
<td>1,461</td>
<td>1,461</td>
<td>1,461</td>
</tr>
</tbody>
</table>

This table presents results obtained from running specification (1) augmented with an interaction term. The variable ‘same caste’ is an indicator equal to 1 if the two firms are in the same caste, 0 otherwise. The variables ‘Old seller’ and ‘Old client’ are indicators whether the (potential) seller, respectively client, is older than the median seller, respectively client, in the sample, the median in the respective samples. All columns include fixed effects for each interaction of the location (postcode) of the seller and the location (postcode) of the client, supplier × year and client × year fixed effects and fixed effects for each interaction of the product sold by the seller and the product sold by the client. Standard errors clustered two-way at the level of the supplier and the client in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.
Table A4: Varna and caste

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>trade</td>
<td>trade</td>
<td>trade</td>
<td>Log. trade</td>
<td>Log. trade</td>
<td>Log. trade</td>
</tr>
<tr>
<td>Same caste group</td>
<td>0.126***</td>
<td>0.064***</td>
<td>0.036***</td>
<td>0.013***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same caste</td>
<td>0.991***</td>
<td>0.968***</td>
<td>0.188***</td>
<td>0.184***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.021)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Obs. (thousand)</td>
<td>202,496</td>
<td>202,496</td>
<td>202,496</td>
<td>1,461</td>
<td>1,461</td>
<td>1,461</td>
</tr>
</tbody>
</table>

This table presents results on larger caste groups' (varnas) effect on trade. Standard errors clustered two-way at the level of the supplier and the client in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.
Table A5: Externally calibrated parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>Labor cost share</td>
<td>0.24</td>
<td>Bernard et al. (2022)</td>
</tr>
<tr>
<td>$\mu$</td>
<td>Markup</td>
<td>1.34</td>
<td>De Loecker et al. 2016</td>
</tr>
<tr>
<td>$X$</td>
<td>Aggregate final demand</td>
<td>1</td>
<td>Normalization</td>
</tr>
<tr>
<td>$\sigma_\varepsilon$</td>
<td>Pair matching cost dispersion</td>
<td>4</td>
<td>Bernard et al. (2022)</td>
</tr>
<tr>
<td>mean $C$</td>
<td>Share of same-caste pairs</td>
<td>0.03</td>
<td>Data</td>
</tr>
</tbody>
</table>