Community Networks and Trade

Johannes Böken, Lucie Gadenne, Tushar Nandi, Marta Santamaria*

February 2023

Abstract

Do communities shape firm-to-firm trade in emerging economies? We study the role of communities in facilitating trade and firm outcomes using data on production networks and firm owners' community (castes) affiliations for the universe of registered 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 underlying mechanisms, we find evidence consistent both with castes alleviating trade frictions and taste-based discrimination against outsiders. Guided by these stylized facts, we develop a model of firm-to-firm trade in which communities affect pair productivity and matching costs and estimate the model using our reduced-form results. Extending the positive effects of castes on trade to *all* potential supplier-client pairs would increase the number of network links by 71% and increase average firm-to-firm sales by 21%.

*Böken and Santamaria: University of Warwick. Gadenne: Queen Mary University of London, Institute for Fiscal Studies and CEPR. Nandi: IISER Kolkata. We would like to thank Guilhem Cassan, Dan Keniston and Tatjana Kleineberg for sharing their caste and surname data, as well as David Atkin, Clare Balboni, Andrew Bernard, Paula Bustos, Stefano Caria, Guilhem Cassan, Mirko Draca, Banu Demir, Simon Franklin, Giacomo de Giorgi, Jonas Hjort, Clement Imbert, Rocco Macchiavello, Yuhei Miyauchi, Tommaso Porzio, Roland Rathelot and numerous seminar participants at the University of Warwick, Queen Mary, the Geneva Trade and Development Workshop (GTDW), University of Geneva, LSE Management lunch and STEG-IGC Annual Conference for helpful comments.

1 Introduction

Most firms in the developing world are, and remain, small (Bloom et al., 2010; Hsieh and Klenow, 2014). This limits their capacity to innovate, upgrade their production technology, export, or even survive (Atkin and Khandelwal, 2020; Ciani et al., 2020; Bassi et al., 2022). There is growing evidence that production networks matter for firm growth: the clients and suppliers firms trade with affect firm size (Bernard et al., 2022), productivity (Atkin et al., 2017; Antràs et al., 2017; Alfaro-Ureña et al., 2022), survival (Hjort et al., 2020) and access to credit (McMillan and Woodruff, 1999). Yet we know very little about the determinants of firms' production networks in developing countries.

Communities may contribute to shaping production networks. A large literature has shown that internal cooperation within communities supports local economic networks (Fafchamps, 2000; Mazzocco and Saini, 2012; Munshi and Rosenzweig, 2016; Fisman et al., 2017; Hjort, 2021; Cassan et al., 2021; Caria and Labonne, 2022). International migrant communities increase international trade across countries (Greif, 1993; Gould, 1994; Rauch, 2001), particularly in the context of high contractual frictions (Rauch and Trindade, 2003). Communities could similarly facilitate firm-to-firm trade within developing countries, where such frictions loom large.

This paper considers the role of community (caste) networks in India in firm-to-firm trade. Using panel data on firm-to-firm transactions and information on the community of the firm owner, we find that firms are substantially more likely to trade, and trade more, when their owners belong to the same community. We show that a large share of the effects of communities on trade is likely due to communities alleviating frictions, although we also find some evidence consistent with taste-based discrimination. Motivated by these stylized facts, we build and estimate a model of network formation in which communities affect both the value of a client-supplier relationship and the cost of forming the relationship. This enables us to quantify the effect of extending the positive effects of castes on trade to all potential supplier-client relationships on production networks, trade and the aggregate economy.

Our contribution is threefold. First, we systematically document the effect of caste networks on firm-to-firm trade. To do so, we use administrative data on the universe of firms paying taxes in the state of West Bengal, India, between 2010 and 2016. The data contains annual transactions between firms, enabling us to map firms' production networks. We obtain community affiliation by searching the names of firm owners in official registries and assigning each last name to a caste community (*jati*) using the anthropological literature (Singh, 1996). Jatis 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 a large effect of castes on trade, both at the extensive and intensive margin. Firms in the same caste are likely to make similar industry and location choices, and experience correlated shocks, so our preferred specification controls flexibly for the joint locations and products sold by suppliers and clients, and allows for arbitrary shocks to all trading partners over time. Our results show 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. We find that castes matter more for the trade of products that are relationship-specific (for whom the hold-up problem is more of a concern), and when trading partners are located in areas with worse-performing courts (making the formal enforcement of contracts harder). Our results suggest that at least two-thirds of the overall effects of castes we estimate can be explained by castes alleviating trading frictions.

We then consider whether part of the effect of castes 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 slightly more likely to exit. Finally, we find no evidence of inaccurate statistical discrimination, as defined by

Bohren et al. (2019b), in our context. Overall, our estimates are consistent both with the idea of castes 'greasing the wheels' of trade in a context with severe contractual frictions, and with caste communities being a source of taste-based discrimination. Interestingly, our results suggest that communities' role in shaping supply networks may gradually fade over the path of development, as institutions that support contracts strengthen, and firms with discriminatory preferences are driven out of the market.

Our third contribution lies in the quantification of the effect of castes on the aggregate economy. To do this, we build on the production network model developed by Bernard et al. (2022) that features a continuum of firms with heterogeneous productivity and relationship capability, and endogenous match formation. We extend this framework to allow for a third source of heterogeneity coming from the firms' caste affiliation. Castes shape production networks in two ways. First, we allow castes to affect the contracting premium that the client has to pay to ensure contract enforcement (Startz, 2021). Second, firms trading within their caste may also face a different matching cost relative to when they trade outside their caste: castes may facilitate the formation of new relationships.

We estimate the model parameters using simulated method of moments. Whilst the estimation of all parameters is simultaneous, we leverage our empirical estimates on the effect of castes on trade to jointly estimate the caste-specific model parameters. As castes facilitate trade in the model, we use the share of these estimates that can be attributed to castes alleviating frictions as (conservative) moments in our estimation. We find that castes slightly increase match profitability (by lowering the contracting premium) and substantially decrease matching costs. Within-caste pairs pay a 3% lower contracting premium when trading and face matching costs that are 92% lower than across-caste pairs. Importantly, we show that both caste parameters are necessary to match the data: a model allowing castes to exclusively affect the contracting premium or matching costs is unable to replicate our reduced form results or match our untargeted moments.

Finally, we use the estimated model to quantify the role of castes in shaping aggregate outcomes. Our main counterfactual scenario considers the effect of extending the positive effect of castes on trade to *all* potential supplier-client pairs. In other words, because our model tells us that same-caste pairs face lower frictions (lower matching costs and contracting premium) than across-caste pairs, our counterfactual considers what would happen if all pairs faced this same low(er) level of frictions. We find large aggregate effects: welfare increases by 36%. The higher trade profitability and lower matching costs increase average firm-to-firm sales by 21% and the number of network connections by 71%. These large effects are due to the fact that the counterfactual reduces trading frictions for the vast majority (96%) of potential pairs in which the supplier and the client come from different castes. Small firms benefit the most, since they have smaller caste networks and therefore smaller production networks at baseline; this counterfactual scenario enables them to substantially expand their trade with other firms.

This paper contributes to the well-established literature considering how firms in developing economies respond to contractual frictions by establishing relational contracts (Macchiavello, 2022), vertically integrating (Woodruff, 2002; Boehm and Oberfield, 2020; Hansman et al., 2020) or building market reputation (Banerjee and Duflo, 2000; Macchiavello and Morjaria, 2015). In particular, a growing literature studies how firms leverage community networks to mitigate these frictions (see for example Fafchamps, 2000; Fisman, 2003; Banerjee and Munshi, 2004; Munshi, 2011, 2014; Fisman et al., 2017; Dai et al., 2020). Our paper builds on this literature by providing the first estimates of the role of community networks in shaping firm-to-firm trade, and quantifying the effects of these networks on the aggregate economy. When investigating mechanisms we find that a large share of the effect of caste on trade that we observe can be explained by castes alleviating market frictions, in line with this literature. Our work is closely related to Boehm and Oberfield (2020) who show that firms' production choices are affected by contracting frictions in India, particularly when producing relationship-specific products in areas with congested courts. Similarly, we find that firms' choices of trading partners are affected by these frictions: firms establish more and stronger trade relationships within their caste relative to outside their caste in high-friction contexts.

We also find evidence consistent with taste-based discrimination along caste lines, suggesting that community networks may simultaneously facilitate trade relationships and distort trade away from firms with small caste networks. This result speaks to the literature documenting the negative effects of ethnic heterogeneity on growth (Alesina and La Ferrara, 2005) by providing micro-level evidence on how communities can introduce trade barriers whist alleviating other trading frictions. Our results are particularly related to Hjort (2014) who finds that workers in Kenyan firms lower their own pay to decrease that of their non-coethnic colleagues. Our evidence that firms with stronger own-caste preferences are more likely to exit similarly point to agents' willingness to sacrifice some economic gains to sustain their community networks (see also La Ferrara, 2002).

Our results build on the existing literature on the role of cultural communities in shaping trade, which typically focuses on how migration networks and cultural proximity across countries affect international trade (Greif, 1993, 2006; Rauch, 2001; Rauch and Trindade, 2003; Bandyopadhyay et al., 2008; Guiso et al., 2009).[1] Our focus on intra-national trade and data on firm-to-firm transactions enables us to provide micro-level evidence of the size of community effects on trade, and investigate the mechanisms underpinning these effects. In ongoing work, Cevallos Fujiy et al. (2023) show that cultural proximity affects trade in a similar context but do not test for whether discrimination (statistical or taste-based) could be driving part of the observed effects.

Finally, we contribute to the literature exploring the aggregate implications of production networks, and their role in shaping firm outcomes such as firm size and productivity through sourcing decisions (Antràs et al., 2017; Bernard et al., 2022), information flows from international buyers (Atkin et al., 2017) and interactions with multinational corporations (Alfaro-Ureña et al., 2022). Previous studies of network formation and development have documented the high costs of acquiring a new trading partner (Bernard et al., 2019; Huneeus, 2018; Startz, 2021). These costs may be higher in the context of low- and middle- income countries (Atkin and Khandelwal, 2020), where contract enforcement institutions are weaker (Nunn, 2007). We extend the parsimonious network formation model in Bernard et al. (2022) to model the role of communities in facilitating trade in such a context.[2] We find that communities in India are quantitatively important in reducing frictions associated with relationship-specific inputs and contract enforcement.

[1] An exception is Combes et al. (2005), who find that migrant communities and business networks in France increase trade across regions.

[2] Recent theoretical advances in this literature have introduced two-sided heterogeneity, in firm productivity and matching costs, to be able to replicate the main patterns in firm-to-firm networks in Norway (Bernard et al., 2018) and Belgium (Bernard et al., 2022).

The rest of the paper is organized as follows. Section 2 describes our context of study and data. 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 and section 5 discusses our model estimation strategy and counterfactual exercises.

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 USD 8,200 (ppp) in 2020, similar to India's national average.[3] The state's official languages are English and Bengali, the latter is spoken by over 86% of the population according to the 2011 census. Our period of study is 2010-2016.

2.1 Community networks in India

India's social architecture is organized around thousands of castes or *jatis*. Internal cooperation within castes supports economic networks: marriages 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 and enforcement constraints, allowing transactions to occur in contexts with severe informational and contractual frictions. The existence of caste networks could, however, simultaneously lead to agents transacting more within caste for preference-based reasons, leading to discrimination and ultimately resource misallocation as agents' economic opportuni-

[3]The structure of the state's economy is also similar to that of India overall, with 21% of GDP in agriculture, 53% in services and 26% in manufacturing, compared to 16%, 54% and 30%, respectively, for the whole of India, according to India's Planning Commission.

ties are constrained if they do not belong to the 'right' caste. Caste networks have indeed been shown to lead to 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 owners' castes. Our main dataset is administrative 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 documents 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 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 remainder we use 3-digit codes.[4] 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 detail 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

[4] When a firm reports several products we keep the product that represents the largest share of its sales.

filing date and, if applicable, the decision date. Our measure of court congestion is an indicator of whether a case had been decided two years after being filed, as our period of study ends in 2016. We aggregate these into an ex-post probability that a case filed in a given district and fiscal year will be decided within the next two years.[5]

We also consider whether castes affect trade in relationship-specific products differently. We use the classification by Rauch (1999) to characterize all products as either homogeneous (traded on an organized exchange or with a reference price) or relationship specific. We use the concordance tables from Liao et al. (2020) to obtain the share of relationship-specific inputs within each NIC 4-digit code, our measure of relationship-specificity for each trading relationship is therefore based on the product sold by the supplier and takes values between 0 and 1. Appendix Figure A2 plots the distribution of our measures of court congestion (panel A) and relationship-specificity (panel B) across all supplier-client pairs.

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. We obtain information on firm owners' caste community by using their tax identification number in the following way. Firms' tax identification number is in the public domain in India and we retrieve information on firm owners' names by querying firm IDs 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). Whilst the concept of caste in South Asia has its roots in Hinduism, non-Hindus are similarly organized in small jati communities and classified as such in Singh (1996); we present results excluding the 12% of firms whose last name suggests they belong to Muslim communities as a robustness check below. [6]

The merge between last names and castes is often not unique: 65% of firm

[5]We consider court congestion in the client's district, in 57% of cases the supplier and the client are located in the same district.

[6]The population of West Bengal is composed mostly of Hindus (71%) and Muslims (27%). Other religions affiliations (Christians, Buddhists) all represent less than 1% of the population.

owners' last names in our data are associated with more than one caste, often because a last name can be associated with different castes in different parts of India. When this occurs, we allocate the first caste in alphabetical order to each last name. Using this method, we obtain information on the firm owner's caste for 75% of firms in the administrative tax data. We consider the robustness of our results to several alternative ways of allocating firms to a caste, by using instead the second caste in alphabetical order or only castes the original source classifies as Bengali. Our baseline measure of common caste affiliation takes a value of 1 if two firm owners are in the same caste, 0 otherwise. We also consider as an alternative a continuous measure of the caste proximity between two firms, by looking at all castes associated with last names and computing the share of castes common to both firms. See Appendix A for more details.

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.[7] 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-client pairs.

Given the number of registered firms in West Bengal, the universe of all potential supplier-client pairs is extremely large and computationally intractable. To consider the effect of castes on the extensive margin of trade we therefore construct a 'potential trade' sample. We first define a client (supplier) as a firm observed on the purchasing (selling) side of a transaction at least once in a given fiscal year - firms are typically 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 product P, we consider the set of all suppliers selling product P and randomly include 25% of them as 'potential suppliers' for this client. This 'potential trade' sample contains 202 million potential annual supplier-client 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

[7] Appendix Figure A1 plots the distribution of the number of firms per caste.

allow, for example, for the possibility that firms adjust their input mix based on the caste of their potential suppliers, we consider a second, larger potential 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 product P' a random 25% of the set of all suppliers seen trading with any client selling product P'.[8]

Table 1 presents descriptive statistics for our transaction data. In the first panel we see that firms have an average of roughly 3 suppliers and 3 clients, but over 400 potential suppliers and clients to choose from, of which 15-18 are from their own caste. There is substantial entry and exit in our data - we observe firms for on average nearly 4 years in a 6 years sample. 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 Effects of castes on trade

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 conditional on the distribution of castes in the potential trade sample. Panel a) plots the share of firms' input purchased from same-caste suppliers (ratio of same-caste purchases to total purchases) as a function of their potential same-caste input share: the share of same-caste suppliers in all their potential suppliers. Panel b) similarly plots the share of firms' sales to same-caste clients as a function of their potential same-caste sales share. Potential clients and suppliers are defined as explained above and weighted by their average network sales. Potential input and sale same-caste shares can therefore be interpreted as how much firms would trade within their caste if they randomly chose their trading partners (Bernard et al., 2019, use

[8] For tractability reasons, we only consider recipes that are used by at least 1% of an industry's suppliers or clients, where each firm is weighted by its total sales.

a similar approach to consider how distance affects firm-to-firm transactions).[9]

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 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 share (sales share) is 4.5% (5.1%) but the average observed same-caste input and sales shares are more than twice as large, at 10.6% and 12.4%, respectively.

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, or facing similar shocks. 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.

Specification. To identify 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:

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

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 if firms are trading when we consider the extensive margin. The indicator $\mathbb{1}(c_i = c_j)$ is equal to 1 if the owners of firms i and j belong to the same caste, 0 otherwise, μ_{it} and μ_{jt} are, respectively, supplier×year and client×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 β) even in the

[9] Our baseline potential trade sample allocates potential suppliers to each client and uses the subsample stratified by client; it is used to produce panel a). To produce panel b) we instead use a subsample stratified by supplier.

absence of a direct effect of caste on firm-to-firm trade for several reasons. 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 choice of industry. We include fixed effects for the interaction of both firms' products to control flexibly for this channel. 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 account for this channel by controlling non-parametrically for the effect of distance on trade by including fixed effects for the interactions of the locations (postcode) of the supplier and the client (Head and Mayer, 2014). Third, firm owners in the same caste may face similar aggregate shocks, which could affect their trading patterns: the role of castes as providers of credit and insurance implies that unobserved shocks to firms 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 β cannot be driven by such caste-level shocks.

Regression results. Panel A of 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 the sample, so they capture 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 columns 2, 3 and 4), firm$\times$ year fixed effects (in columns 3 and 4) 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.

Panel B of Table 2 presents estimates of the effect of castes on the intensive margin of trade, 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 (18%) with each other. Overall, results in Table 2 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. These effects of castes on trade are very large, though of comparable magnitude to the estimated effect of castes on another 'matching market': Banerjee et al. (2013) find that the probability that individuals respond to letters received in response to matrimonial ads increases by 45-60% when the sender is of the same caste. The effect of castes on the intensive margin of trade is also comparable to, albeit smaller than, the effect of speaking the same language in international trade (45-50% increase in trade, see Head and Mayer, 2014).

We consider the robustness of our estimates to our variable definition, sample construction, and specification choices in Appendix Tables A1 and A2. We exclude firms whose products are not defined at the detailed 4-digit level, consider several alternative assignments of last names to castes and a continuous measure of caste proximity, as explained above, exclude the largest 3 castes and all firms with no same-caste potential partners, and consider standard errors two-way clustered at the level of the client's industry and location. Results are remarkably similar across specifications and samples. For the extensive margin results we additionally consider alternative ways to define firms' sets of 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'-based definition of potential trading partners in the spirit of Atalay et al. (2019), described above, we no longer constrain a firm's set of potential suppliers to only include sellers of products this firm is observed buying. We find a larger effect, suggesting that firms' caste networks may also affect which inputs they buy. Finally, Appendix Table A3 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.[10] We find a small effect of *varnas* on trade of roughly 7% the magnitude of our baseline caste effect, which remains unchanged when we allow *varnas* to also affect trade.

[10]We distinguish between Scheduled Castes, Scheduled Tribes, Other Backward Castes and others as these are the groups that are defined in Indian law.

3.2 Mechanisms

Having established a large effect of caste on the extensive and intensive margins 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 providing 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. 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.[11]

Table 3 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 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 contractual frictions: trade of perfectly homogeneous products

[11] Appendix Figure A2 plots the distribution of the relationship-specificity score and court congestion separately for all pairs in our potential trade sample and only pairs that are observed trading, we see substantial overlap between the two distributions.

in areas in which courts complete all cases within two years. 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.[12] This test builds on the argument in Becker (1957) that firms with strong discriminatory preferences will forego profits by indulging these preferences and, in competitive markets, will eventually be forced out. In our context, this implies that firms with strong same-caste preferences (proxied for by a same-caste input share above industry average) will be less likely to survive. Specifically, we estimate a Cox regression of firm exit hazard on same-caste input share, relative to the industry average, whilst flexibly controlling for firms' products, location and size.[13] This approach follows that of Weber and Zulehner (2014), who test whether firms with a strong taste for discrimination (proxied by a low share of female employees) are less likely to fail in Austria.

Results on firm survival as a function of their caste preference are presented in Table 4. We see that firms with strong preferences for trading within their caste are slightly more likely to exit. A one standard deviation increase in a firm's same-caste input share (relative to the industry average) is associated with a 2.1% 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. We find a similar results when looking at the relationship between firm exit and same-caste sales

[12] 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, and while they are still required to file taxes, 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 assumes the tax authorities will ignore the fact that it has stopped filing taxes. In both cases, an exit is a sign of poor profitability.

[13] Formally, we control throughout for firm age and size and stratify our hazard model using information on firms' location, products sold, and size decile. This allows the baseline hazard to vary non-parametrically between strata. In our preferred specification, column (4) of Table 4, we only compare firms within the same postcode, selling the same product and in the same decile of the size distribution, yielding a total of 59,936 unique groups.

share in Appendix Table A4 (5.7% higher risk of exit for a 1 standard deviation increase in same-caste sales share).

Inaccurate 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 whereby most firms 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 and incorrectly expect them to be worse-performing trading partners compared to those from their own caste. Bohren et al. (2019b) show that looking at the dynamic patterns of discrimination helps uncover biased beliefs, because individuals holding such beliefs will change their behavior 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 trading partners from their own caste are better performers relative to partners from other castes, we should see within-caste relationships fail to thrive relative to across caste relationships.

In Appendix Figure A3 we investigate whether the effect of caste on trade fades as trading partners have more experience of each other. Looking at a sample of newly formed pairs we find that the effect of caste on both the extensive and intensive margins of trade are stable over 5 years. There is no evidence of effects decreasing as firms learn more about each other; this suggests inaccurate statistical discrimination isn't driving our results. Consistent with this, we find no evidence that caste networks affect trade less when either the client or the supplier has more experience or a better-established reputation (proxied for by time since registration with the tax authorities, see Appendix Table A5).

Our evidence regarding the mechanisms underlying the effects of castes on trade, whilst suggestive, nevertheless raises the possibility that these effects could gradually decrease over time and/or over the course of economic development, as contract-enforcement institutions improve and firms with discriminatory preferences are driven out of the market. Appendix Figure A4 plots the effect of castes on the extensive and intensive margins of trade separately for each of the six years in our sample. We see no evidence of the effect decreasing (or increasing) over time. This may be because there were no major institutional changes in West Bengal that could have improved contract enforcement during our period, and because the effect of higher-than-average caste preferences on exit we estimate is too small to affect the composition of firms over a short period.

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 aggregate effect of castes on trade.

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

We construct a model of supplier-client networks with two-sided firm heterogeneity and endogenous match formation, built on Bernard et al. (2022). This framework is well suited to the main characteristics of the production network in West Bengal. First, the distributions of firm and network sizes are highly dispersed, suggesting a high degree of firm heterogeneity. Second, firms with more clients have higher sales and higher sales per client, showing that firm size is associated with both the ability to adopt new clients and the ability to sell to those clients. Third, suppliers with more clients match with clients who have fewer suppliers on average, known as negative degree assortativity. This is a feature of production networks that is well captured by parsimonious models of firm matching, such as the one below, where a match is formed when the profits of the match are larger than the costs. We provide further details on the characteristics of the production network and how they are captured by the model in Appendix B.

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 in the model. First, firms have different productivity levels, that help them produce inputs more or less 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 different caste communities. We specify how castes affect trade in what follows.

4.1.1 Technology and Demand

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

$$y(i) = \kappa z(i) l(i)^{\alpha} v(i)^{1-\alpha}, \tag{2}$$

where $y(i)$ is the quantity of output produced by firm i, $z(i)$ is exogenously given productivity, $l(i)$ is the amount of labor used by firm i, α is the labor share, and $\kappa > 0$ is a normalization constant.[14] $v(i)$ is the bundle of intermediate inputs used by the firm in production, given by:

$$v(i) = \left(\int_{\mathcal{S}(i)} \nu(i,k)^{\frac{(\sigma-1)}{\sigma}} dk \right)^{\frac{\sigma}{\sigma-1}}, \tag{3}$$

where $\nu(i,k)$ is the quantity that firm i purchases from firm k, $\mathcal{S}(i)$ 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 $P(i) = \left(\int_{\mathcal{S}(i)} p(k)^{1-\sigma} dk \right)^{1/(1-\sigma)}$, 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 more efficient suppliers (those that charge a low price $p(k)$ for their inputs) and when it can source from a larger set of suppliers. Thus, a firm's marginal cost of production is decreasing in its productivity, the size of its supplier set, and the average productivity of its suppliers.

We set the wage as the numeraire ($w = 1$) and express the marginal unit cost at which firm i can sell a unit to firm j as:

$$u(i,j) = \frac{P(i)^{1-\alpha}}{z(i)\delta_z^{1-\mathcal{C}_{i,j}}}, \tag{4}$$

where $P(i)$ is the input price index of firm i and $\mathcal{C}_{i,j}$ is an indicator such that $\mathcal{C}_{i,j} =$

[14] The constant is $\kappa = \alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}$

0 if firms i and j belong to the same caste, 1 otherwise. Parameter $\delta_z^{1-\mathcal{C}_{i,j}}$ captures the potential effect of caste communities on the contracting premium. In contexts with high frictions and low enforcement, clients may want to pay slightly higher prices to ensure that the supplier fulfills the contract, especially when interactions are repeated (see Startz, 2021). In our model, $\frac{1}{\delta_z}$ is the contracting premium paid in same-caste pairs relative to different-caste pairs.[15] If $\delta_z > 1$, same-caste pairs face a lower contracting premium (conditional on firm characteristics), e.g., due to higher trust or lower risk.

Final demand. Final consumers have a CES utility function with the same elasticity of substitution σ across output varieties. We assume that the representative consumer is the shareholder of all firms, so that aggregate profits Π 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.[16] Given our assumption about the production function and the demand for intermediates, we can solve for the sales from firm i to firm j:

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

where $M(j) = \int_{S(j)} m(k,j)dk$ is total intermediate purchases by firm j, and $p(i,j)$ is the price at which firm i sells one unit to firm j.

The market structure of monopolistic competition means that firms will choose to charge a constant mark-up over the marginal unit cost (equation (4)) such that the price that firm i sets to sell to firm j is given by $p(i,j) = \mu \times u(i,j)$, where $\mu = \sigma/(\sigma-1)$, is the constant mark-up. After rearranging, sales from i to j can

[15] To see this, notice that the term $\delta_z^{1-\mathcal{C}_{i,j}} = 1$ when i and j do not belong to the same caste.

[16] Each firm sells its final output as intermediate input to other firms and to final consumers. The sourcing and producing of intermediate varieties happen simultaneously.

be expressed as:

$$m(i,j) = \left[\frac{z(i)\delta_z^{1-\mathcal{C}_{i,j}}}{\mu P(i)^{1-\alpha}} P(j) \right]^{\sigma-1} M(j). \tag{6}$$

Taking logs of equation (6), we see that the model delivers the same log-linear expression for firm-to-firm sales as the specification we use in our empirical section 3 above, equation (1).

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, paid in units of labor. In the model, firm productivity z and the cost of forming a match F are potentially correlated, and dG (λ) denotes the (multivariate) density of λ. Let us define the link function $l(\lambda, \lambda')$ as the share of supplier-client pairs of type (λ, λ') that match in a trade relationship.

Backward fixed point. Given a fixed set of supplier-client links, we can find the trade equilibrium by solving for two fixed points sequentially. The first fixed point is the set of equations that define the equilibrium input price index. Given the pricing rule $p(\lambda, \lambda') = \mu c(\lambda, \lambda')$ and the marginal unit cost (4), the input price index can be solved for by iterating on a backward fixed point problem:

$$P(\lambda)^{1-\sigma} = \mu^{1-\sigma} \int P(\lambda')^{(1-\sigma)(1-\alpha)} \left(z(\lambda')\delta_z^{1-\mathcal{C}(\lambda,\lambda')} \right)^{\sigma-1} l(\lambda', \lambda) dG(\lambda'). \tag{7}$$

The input cost index of a firm of type λ, $P(\lambda)$, will be a function of the input cost index and productivity of all its suppliers, $P(\lambda')$ and $z(\lambda')$, through the network link structure $l(\lambda, \lambda')$.

Forward fixed point. The second fixed point determines firm total sales. We know that the sales of a type λ firm are the sum of sales to final and intermediate demand: $S(\lambda) = \mathcal{F}(\lambda) + \int m(\lambda, \lambda') l(\lambda, \lambda') dG(\lambda)$. Final demand is given by the demand of the representative final consumer $\mathcal{F}(\lambda)$ = p $(\lambda)^{1-\sigma}\mathcal{P}^{\sigma-1}X$, where X is aggregate income.[17] Due to the structure of the production function, total input purchases are given by a fixed fraction of total sales: $M(\lambda) = S(\lambda)(1-\alpha)/\mu$. We can use this expression together with the marginal unit cost function (4) and the final demand function to solve for total sales for firm λ:

$$S(\lambda) = \left(\frac{\mu z(\lambda)}{P(\lambda)^{1-\alpha}}\right)^{\sigma-1}\left(\frac{X}{\mathcal{P}^{1-\sigma}} + \frac{1-\alpha}{\mu}\int \frac{S(\lambda')}{P(\lambda')^{1-\sigma}}\delta_z^{1-\mathcal{C}(\lambda,\lambda')(\sigma-1)} l(\lambda,\lambda')dG(\lambda')\right). \tag{8}$$

Sales of a type λ firm depend on aggregate income, X, the firm's productivity and input price index, $z(\lambda)$ and $P(\lambda)$, and the sales and input prices of its clients, $S(\lambda')$ and $P(\lambda')$, through the network link structure $l(\lambda,\lambda')$. In addition, the sales of each supplier will be affected by whether the supplier and the client have the same caste affiliation. Bernard et al. (2022) provide proof of the existence and uniqueness of the equilibrium.

4.1.4 Firm-to-Firm Matching

We discuss now the solution of the general equilibrium when we allow for the firm-to-firm network to be endogenous, such that suppliers match with clients if and only if the profits from doing so are positive. To form a link, the supplier must pay a baseline match fixed cost $F\varepsilon$ for every client it chooses to sell to, where F is supplier-specific and ε is an idiosyncratic shock that varies across supplier-client pairs.[18] In addition, we introduce a parameter to capture the effect of caste affiliation on the matching fixed cost. The total cost of creating a trade relationship is $F\varepsilon e^{\delta_F(1-\mathcal{C}(\lambda,\lambda'))}$, where $\mathcal{C}(\lambda,\lambda') = 0$ indicates that the pair (λ,λ') belongs to the same caste, 1 otherwise. If $\delta_F \neq 0$, the cost of creating a new trading relationship will be different for same-caste pairs and different-caste pairs.

Given these assumptions on the matching technology, the share of supplier-client pairs (λ,λ') that match and trade with each other is:

$$l(\lambda,\lambda') = \int \mathbb{1}\left[ln\varepsilon < ln\pi(\lambda,\lambda') - lnF + (1-\mathcal{C}(\lambda,\lambda'))\delta_F\right] dH(\varepsilon), \tag{9}$$

[17] The price index faced by the final consumer is equal to $\mathcal{P}^{1-\sigma} = \int p(\lambda)^{1-\sigma}dG(\lambda) = \mu^{1-\sigma}\int P(\lambda)^{(1-\sigma)(1-\alpha)}z(\lambda)^{\sigma-1}dG(\lambda)$

[18] The introduction of this 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)).

where $\mathbb{1}[]$ is the indicator function, $dH(\varepsilon)$ denotes the density of ε, and the gross profits from the potential match are:

$$\pi(\lambda, \lambda') = \frac{m(\lambda, \lambda')}{\sigma}. \tag{10}$$

This expression gives us the trade probability for a pair type (λ, λ') which depends on the profitability of the match and on the matching costs. Note that both caste parameters enter this equation and affect trade probabilities. The inverse contracting premium term δ_z affects the match gross profits; the caste matching cost δ_F changes the matching costs. Equation (9) therefore highlights how both caste parameters could be driving the effect of caste on the extensive margin of trade we observe.

Given the gross profits, the matching costs and the pair shocks, this link function is also a fixed point problem.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 with 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 supplier-client pairs that match according to equation (9).
(iv) Go back to step (ii) and repeat 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 use to interpret our empirical evidence in section 3.

1. Firm-to-firm sales (intensive margin)

$$ln\Big(m(\lambda, \lambda')\Big) = \underbrace{(1 - \mathcal{C}(\lambda, \lambda'))}_{\text{Caste indicator}}(\sigma - 1) ln(\delta_z) + \underbrace{(\sigma - 1) ln\left[\frac{z(\lambda)}{\mu P(\lambda)^{1-\alpha}}\right]}_{\text{Client FE}} + \underbrace{ln\left[\frac{M(\lambda')}{P(\lambda')^{1-\sigma}}\right]}_{\text{Supplier FE}} \tag{11}$$

Conditional on client and supplier fixed effects, our positive estimate of effect of castes on the intensive margin of trade is evidence of a higher trading value and a lower contracting premium between firms in the same caste ($1/\delta_z < 1$). Calibrating σ then enables us to identify δ_z.

2. Firm-to-firm trading probabilities (extensive margin)

$$l(\lambda,\lambda') = \int \mathbb{1}\left[ln\varepsilon < \underbrace{ln\left(\frac{m(\lambda,\lambda')}{\sigma}\right)}_{\text{Match profits}} - \underbrace{lnF}_{\text{Firm Matching cost}} + \underbrace{(1-\mathcal{C}(\lambda,\lambda'))\delta_F}_{\text{Caste matching cost}}\right] dH(\varepsilon), \tag{12}$$

We find a positive effect of castes on the extensive margin of trade. This expression clarifies that this could be due to both a lower contracting premium for same-caste pairs ($1/\delta_z < 1$) and/or a lower matching cost for these pairs ($\delta_F < 0$).

In the next section we explain how we estimate the model and use it to conduct counterfactual exercises.

5 Estimation and Results

This section provides a model-based quantification of the aggregate effects of caste communities on trade. We start by estimating the model using our production network data and the estimated effects of castes on trade presented in section 3. This yields estimates of the underlying parameters governing the effect of castes on trade, δ_z and δ_F. We then use the model to consider two counterfactual scenarios.

5.1 Simulated Method of Moments

We estimate the model using simulated method of moments (SMM). We assume that firm productivity z and matching costs F are distributed joint log-normal with expectations $\mu_{lnz} = 0$ and μ_{lnF}, standard deviations σ_{lnz} and σ_{lnF}, and correlation coefficient ρ. We calibrate several parameters by drawing on the existing literature. We follow Boehm and Oberfield (2020) in calibrating the labor cost share α to the Indian context, De Loecker et al. (2016) to assign a value of the markup μ, Bernard et al. (2022) for the standard deviation of the idiosyncratic matching cost $\sigma_{ln\epsilon}$, and normalize aggregate final demand X to 1. We calibrate the distribution of firms' caste affiliations to replicate the caste distribution in our data, including the share of same-caste pairs in the potential trade data (3.57%, see Table 1). We simulate the model with 300 firms, allocating firms to caste communities in the following way: the two largest castes contain 10% of firms each, five medium castes contain 8%, 6%, 4% 2% and 1% of firms each, and the remaining firms are assigned to small communities with only two firms in each. Appendix Table A6 summarizes the externally calibrated parameters, their definitions, and the values assigned to them.

There remain six parameters to be estimated $\Gamma = \{\mu_{lnF}, \sigma_F, \sigma_z, \rho, \delta_z, \delta_F\}$. We choose six targeted moments in the data to estimate Γ, presented in the first column of Table 5. Whilst all moments jointly pin down all estimated parameters, there is an intuitive mapping from the targeted moments to model parameters. First, the mean and variance of the log number of clients help identify the mean and variance of the matching costs, F, while the variance of network sales helps identify the variance of productivity. The correlation between productivity and matching costs, ρ, is related to the strength of the relation between the average market share across clients and the number of clients a firm has. We therefore use the slope coefficient from the regression of average market share across clients on the number of clients as our fourth targeted moment, following Bernard et al. (2022).[19] Finally, the estimated effects of castes on the intensive and extensive margins of trade enable us to estimate the relative contracting premium parameter δ_z and the caste-specific matching cost δ_F.

The mapping from our estimates of the effect of castes on trade in from Tables 2 and 3 to the model parameters governing the role of castes warrants further discussion. Our model is designed to consider how communities may facilitate trade by making matches more profitable, easier to form, or both. Our empirical evidence suggests that a large part of the observed effect on trade can indeed be explained by castes facilitating trade by alleviating frictions in firm-to-firm

[19] In a model with productivity as the single source of firm heterogeneity, more productive firms have more clients and also have higher average market shares over their clients. As shown in Bernard et al. (2022), a flatter (or more negative) slope coefficient in the regression of average market share on number of clients suggests that firms with more clients, who face lower matching costs, are relatively less productive and do not achieve high market shares. To rationalise this empirical pattern, productivity and firm-specific matching costs must be positively correlated. We estimate a slope coefficient of 0.01, suggesting a positive but small relationship between average market share and the number of clients. For more details, see figure A8 in the Appendix.

markets, but perhaps not all of it: we also find evidence suggesting that taste-based discrimination against firms from other castes may play a role. Columns 3 and 6 of Table 3 suggest that roughly one-third of the effect of castes on trade remains in contexts with minimal frictions (uncongested courts and homogeneous products). We cannot, of course, rule out that other frictions are still important in those contexts, so that part of the effect of castes for homogeneous products and uncongested courts could still be capturing their role in facilitating trade, as well as a taste-based discrimination. But our results suggest that at least two-thirds of the estimates can be attributed to castes alleviating frictions. We therefore take a conservative approach and use two-thirds of our preferred estimates of the effect of castes on the intensive and extensive margins of trade (those in the last columns of Table 2) as moments in the estimation: 0.66 for the extensive margin and 0.12 for the intensive margin.[20]

Taking logs of our model expression for firm-to-firm sales (11) we see that our specification (1) for the effect of castes on log trade volumes identifies the parameter δ_z if there are no pair-specific unobserved determinants of trade profitability correlated with the likelihood that both trading parties belong to the same caste. Similarly, our estimate of the effect of castes on the extensive margin of trade is the empirical equivalent of our model expression for the share of supplier-client pairs that trade (expression (12)). As highlighted above, the positive effect of communities on the extensive margin could be driven by both a lower relative contracting premium or by a lower matching cost. Therefore, it is essential to jointly estimate both caste-related parameters rather than using the coefficients separately as their empirical counterparts. Our SMM strategy relies on the structure of the model and the magnitudes of these two coefficients to jointly identify the relative contracting premium, $1/\delta_z$, and the caste-specific matching cost, δ_F.

Overall, our model enables us to estimate the relative contracting premium and matching caste parameters that are consistent with the production network moments as well as the reduced-form evidence presented in section 3. Collecting the targeted empirical moments in vector x and the simulated moments in vector

[20] Future work could expand the model to include contract enforcing frictions as well as taste-based discrimination, in order to quantify their relative importance on trade.

$x^s(\Gamma)$, the SMM estimates for Γ solve:

$$\arg\min_{\Gamma}(x - x^s(\Gamma))'(x - x^s(\Gamma)). \tag{13}$$

5.2 Model estimation results

Table 5 reports the results from the SMM estimation. Column 1 reports the value of the targeted and untargeted moments in the data. Column 2 reports our estimated parameters and value of the simulated moments. We find that both productivity heterogeneity and fixed costs heterogeneity are important, but the variance of the matching costs is much higher than the variance of productivity, in line with recent evidence on the importance of the firm network for firm outcomes (Bernard et al., 2022). We also find evidence of a positive correlation between productivity, z, and matching costs, F, again consistent with estimates in Bernard et al. (2022).

Crucially, our estimates indicate that communities play a role in both the value of matches (through the contracting premium) and the likelihood that they occur (through matching costs). We find that the relative contracting premium is $1/\delta_z = 0.968$, meaning that within-caste trade pairs pay a 3% lower contracting premium than pairs trading across-castes. Our estimate of δ_F is -2.606, implying that matching costs are 92% lower (1-exp(-2.606)=0.92) for same-caste pairs. Our estimated parameters provide a very good model fit, as all targeted moments are well matched. In addition, the model performs well in untargeted moments related to the firm-to-firm network. The model predicts a large average (log) number of same-caste clients (-3.624 relative to -2.510 in the data). We also replicate the strong negative degree assortativity that we find in the West Bengal trade network (slope of -0.284 relative to -0.467 in the data).

Columns 3 and 4 estimate alternative models in which we restrict the effect of communities to operate only through a single margin. In column 3 we only allow for an effect of castes on the contracting premium, not on matching costs (setting $\delta_F = 0$). In column 4 we only allow for an effect of castes on matching costs, not on the contracting premium (setting $\delta_z = 1$). As we can see from the targeted and untargeted moments, neither of these restricted models are able to explain what we see in the data. The model with no effect of castes on matching costs overestimates the effect of castes on the intensive margin (simulated estimate of 0.326) and underestimates both the extensive margin effect (simulated estimate of -0.142) and the number of same-caste clients (-4.376, compared to -2.510 in the data). The model with no effect of castes on the contracting premium cannot match our observed intensive margin effect (simulated estimate of 0.027). These results indicate that castes affect both the matching costs that firms face and the contracting premium needed to enforce the contract between client and supplier.

5.3 Counterfactuals

In this section, we use our estimated model to investigate how castes shape aggregate outcomes such as firm sales, firm connections and welfare. Our empirical results show that, when contractual frictions are high, firms in the same caste are more likely to start a trading relationship and trade larger values than firms in different castes, highlighting the role of castes communities as trade facilitators. We perform two counterfactuals to explore the aggregate implications of this trade-facilitating role. Our first counterfactual asks *What would be the aggregate implications of extending the positive effects of castes on trade to* all *potential supplier-client pairs?* Our counterfactual 1 is thus a scenario in which all supplier-client pairs enjoy the benefits of within-caste trade. Since our model tells us that same-caste pairs face lower frictions (lower matching costs and contracting premium) than across-caste pairs, this counterfactual considers what would happen if all pairs faced this same low(er) level of frictions. Our second counterfactual asks *What would be the aggregate implications of removing the positive effects of castes on trade for same-caste pairs?* In this scenario no potential supplier-client pairs can benefit from the within-caste lower contracting premium and matching costs. This counterfactual tells us about the aggregate effects of removing castes as trade facilitators. Formally, our counterfactual 1 sets the caste indicator $\mathcal{C}_{i,j}$ to $\mathcal{C}_{i,j} = 0$ for all supplier-client pairs, so that all firms are assumed to belong to the same caste, and counterfactual 2 sets $\mathcal{C}_{i,j} = 1$ for all pairs, so that all firms are assumed to be alone in their caste.

Panel A of Table 6 reports the results for both counterfactuals in columns 1 and 2. The outcomes are reported relative to the levels of the baseline model where caste affiliation is calibrated to match the observed caste distribution, and the parameters are estimated as explained in the previous section. We find large aggregate effect of extending the positive effects of castes on trade to all potential supplier-client pairs (counterfactual 1, column 1): welfare in the economy goes up by 36%. This comes from a 71% increase in total firm-to-firm connections, and an input price reduction of 14%. As a result of the lower contracting premium and the lower matching costs, average firm-to-firm trade (network sales) grows by 21%. The reason for this large effect is that most potential supplier-client pairs (96.5%) in the data do not belong to the same caste. Thus, by extending the positive effects of castes as trade-facilitators to all potential pairs, we are increasing the trading profitability and the matching ability for almost 97% of pairs in the sample.

Column 2 of panel A reports the results of counterfactual 2: removing the positive effects of castes on trade for all potential supplier-client pairs. This change would have more moderate effects, due to the small number of same-caste pairs in the data. If we eliminated the lower contracting premium and the lower matching costs that same-caste pairs enjoy, this would reduce welfare by 1.1%. This reduction would come from 2.5% lower connections with clients and 2% lower average firm-to-firm sales.

In panel B of Table 6, we provide a decomposition of the effects of counterfactual 1 (extending the positive effects of castes on trade) into the effects of extending the positive effects of castes on matching costs and on the contracting premium, respectively. We find that most of the effect comes from the reduction in the matching cost for all across-caste pairs. Keeping differences in the contracting premium but reducing the matching cost for all pairs would provide 100% of the increase in sales and network connections, and 82.6% of the welfare gains. On the contrary, providing all pairs with a 3% lower contracting premium but keeping the different matching costs would have much more modest effects on aggregate variables.

5.4 Counterfactual effects by firm size

Finally, we investigate the effects of our counterfactual 1 (in which all supplier-client pairs enjoy the benefits of within-caste trade) on the distribution of firm size (total network sales). Panel (a) in Figure 2 plots the distribution of firm size at baseline (continuous blue line) and under this counterfactual scenario (dashed red line). We see that the firm size distribution shifts to the right and becomes less dispersed: there is an increase in the number of middle-sized firms and fewer smaller firms. The right tail of the distribution is mostly unchanged.

This shift in the distribution can be explained by the results in panels (b) and (c) of Figure 2. Panel (b) plots the change in average network sales under the counterfactual as a function of firm size at baseline. Average network sales grow for all firm sizes, but nearly twice as much for small firms compared to large firms. Panel (c) plots the change in the number of clients as a function of baseline firm size. We see that small firms nearly triple the number of clients they sell to, with smaller increases for larger firms. This can be explained by the fact that small firms suffer more from contracting and matching frictions at baseline because of their smaller caste networks and lower initial productivity. Reducing these frictions allows them to expand their firm networks substantially relative to their starting point.

Overall, our results point to a potentially substantial impact of removing across-caste frictions in firm-to-firm networks for development outcomes, such as firm size, firm networks and aggregate welfare. Using our model estimates, we find large aggregate benefits of extending the trade-facilitating effects of castes to all firms in the sample. To design policies that provide the gains highlighted by our counterfactual scenarios, future work should be directed towards a better understanding of the reasons and mechanisms through which communities shape and facilitate trade.

6 Conclusion

This paper considers 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 owners' communities, we find that when two firms belong to the same community they are twice as likely to trade and, conditional on trading, trade 20% more. We provide evidence consistent both with communities alleviating frictions and with taste-based discrimination. Overall, our results suggest that castes do 'grease the wheels' of firm-to-firm trade, allowing transactions to occur despite high frictions, and that firm owners are willing to sacrifice some economic gains to allow same-caste preferences to endure.

To understand the aggregate effects of communities on the economy via production networks, we build a model of network formation in which communities affect both the profitability of a client-supplier relationship and the cost of forming the relationship. Estimating model parameters using our reduced-form evidence, we find that extending the positive effects of communities on trade to all potential supplier-client relationships would substantially thicken production networks and lead to firm growth, particularly amongst smaller firms.

References

Alesina, A. and E. La Ferrara (2005): "Ethnic diversity and economic performance," *Journal of economic literature*, 43, 762–800.

Alfaro-Ureña, A., I. Manelici, and J. P. Vasquez (2022): "The Effects of Joining Multinational Supply Chains: New Evidence from Firm-to-Firm Linkages," 137, 1495–1552.

Anderson, S. (2011): "Caste as an Impediment to Trade," *American Economic Journal: Applied Economics*, 3, 239–63.

Antràs, P., T. C. Fort, and F. Tintelnot (2017): "The Margins of Global Sourcing: Theory and Evidence from US Firms," 107, 2514–2564.

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

Atalay, E., A. Hortaçsu, M. J. Li, and C. Syverson (2019): "How wide is the firm border?" *The Quarterly Journal of Economics*, 134, 1845–1882.

Atkin, D. and A. K. Khandelwal (2020): "How Distortions Alter the Impacts of International Trade in Developing Countries," *Annual Review of Economics*, 12, 213–238.

Atkin, D., A. K. Khandelwal, and A. Osman (2017): "Exporting and Firm Performance: Evidence from a Randomized Experiment*," 132, 551–615.

Bandyopadhyay, S., C. C. Coughlin, and H. J. Wall (2008): "Ethnic Networks and US Exports*," *Review of International Economics*, 16, 199–213.

Banerjee, A., E. Duflo, M. Ghatak, and J. Lafortune (2013): "Marry for What? Caste and Mate Selection in Modern India," *American Economic Journal: Microeconomics*, 5, 33–72.

Banerjee, A. and K. Munshi (2004): "How Efficiently Is Capital Allocated? Evidence from the Knitted Garment Industry in Tirupur," *The Review of Economic Studies*, 71, 19–42.

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

Bassi, V., R. Muoio, T. Porzio, R. Sen, and E. Tugume (2022): "Achieving Scale Collectively," 90, 2937–2978.

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

Bernard, A. B., E. Dhyne, G. Magerman, K. Manova, and A. Moxnes (2022): "The Origins of Firm Heterogeneity: A Production Network Approach," 130, 1765–1804.

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

Bernard, A. B., A. Moxnes, and K. H. Ulltveit-Moe (2018): "Two-Sided Heterogeneity and Trade," *The Review of Economics and Statistics*, 100, 424–439.

Bloom, N., A. Mahajan, D. McKenzie, and J. Roberts (2010): "Why Do Firms in Developing Countries Have Low Productivity?" *American Economic Review*, 100, 619–23.

Boehm, J. and E. Oberfield (2020): "Misallocation in the Market for Inputs: Enforcement and the Organization of Production," *The Quarterly Journal of Economics*, 135, 2007–2058.

Bohren, J. A., K. Haggag, A. Imas, and D. G. Pope (2019a): "Inaccurate Statistical Discrimination: An Identification Problem," NBER Working Papers 25935, National Bureau of Economic Research, Inc.

Bohren, J. A., A. Imas, and M. Rosenberg (2019b): "The Dynamics of Discrimination: Theory and Evidence," *American Economic Review*, 109, 3395–3436.

Caria, S. and J. Labonne (2022): "Village Social structure and Labor Market PerformanceEvidence from the Philippines," Tech. rep., Mimeo, University of Warwick.

Cassan, G. (2020): "The Economics of Caste," Tech. rep., Chapter prepared for the Oxford Handbook of Caste in Contemporary/Modern Times, Surinder S. Jodhka and Jules Naudet (editors).

Cassan, G., D. Keniston, and T. K. Kleineberg (2021): "A Division of Laborers : Identity and Efficiency in India," Policy Research Working Paper Series 9544, The World Bank.

Cevallos Fujiy, B., G. Khanna, and H. Toma (2023): "Cultural Proximity and Production Networks," STEG Working Paper.

Ciani, A., M. C. Hyland, N. Karalashvili, J. L. Keller, A. Ragoussis, and T. T. Tran (2020): *Making It Big: Why Developing Countries Need More Large Firms*, The World Bank.

Combes, P.-P., M. Lafourcade, and T. Mayer (2005): "The trade-creating effects of business and social networks: evidence from France," 66, 1–29.

Dai, R., D. Mookherjee, K. Munshi, and X. Zhang (2020): "The Community Origins of Private Enterprise in China," Boston University - Department of Economics - The Institute for Economic Development Working Papers Series dp-320, Boston University - Department of Economics.

De Loecker, J., P. K. Goldberg, A. K. Khandelwal, and N. Pavcnik (2016): "Prices, Markups, and Trade Reform," 84, 445–510.

Fafchamps, M. (2000): "Ethnicity and credit in African manufacturing," *Journal of Development Economics*, 61, 205–235.

Fisman, R., D. Paravisini, and V. Vig (2017): "Cultural Proximity and Loan Outcomes," *American Economic Review*, 107, 457–92.

Fisman, R. J. (2003): "Ethnic Ties and the Provision of Credit: Relationship-Level Evidence from African Firms," *The B.E. Journal of Economic Analysis & Policy*, 3, 1–21.

Gadenne, L., T. Nandi, and R. Rathelot (2022): "Taxation and Supplier Networks: Evidence from India," Tech. rep., CEPR Discussion Paper 13971.

Gould, D. M. (1994): "Immigrant Links to the Home Country: Empirical Implications for U.S. Bilateral Trade Flows," 76, 302.

Greif, A. (1993): "Contract Enforceability and Economic Institutions in Early Trade: the Maghribi Traders' Coalition," *American Economic Review*, 83, 525–48.

——— (2006): *Institutions and the path to the modern economy: Lessons from medieval trade*, Cambridge University Press.

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

Hansman, C., J. Hjort, G. León-Ciliotta, and M. Teachout (2020): "Vertical Integration, Supplier Behavior, and Quality Upgrading among Exporters," *Journal of Political Economy*, 128, 3570–3625.

Head, K. and T. Mayer (2014): "Gravity Equations: Workhorse,Toolkit, and Cookbook," in *Handbook of International Economics*, Elsevier, vol. 4, 131–195.

Hjort, J. (2014): "Ethnic divisions and production in firms," *The Quarterly Journal of Economics*, 129, 1899–1946.

——— (2021): "Ethnic Investing and the Value of Firms," CEPR Discussion Papers 16316, C.E.P.R. Discussion Papers.

Hjort, J., V. Iyer, and G. de Rochambeau (2020): "Informational Barriers to

Market Access: Experimental Evidence from Liberian Firms," NBER Working Papers 27662, National Bureau of Economic Research, Inc.

Hsieh, C.-T. and P. J. Klenow (2014): "The Life Cycle of Plants in India and Mexico," *The Quarterly Journal of Economics*, 129, 1035–1084.

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

Iyer, R. and A. Schoar (2015): "Ex post (in) efficient negotiation and breakdown of trade," *American Economic Review*, 105, 291–94.

La Ferrara, E. (2002): "Self-help Groups and Income Generation in the Informal Settlements of Nairobi," *Journal of African Economies*, 11, 61–89.

Liao, S., I. S. Kim, S. Miyano, and H. Zhang (2020): *concordance: Product Concordance*, r package version 2.0.0.

Macchiavello, R. (2022): "Relational Contracts and Development," *Annual Review of Economics*, 14, 337–362.

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

Mazzocco, M. and S. Saini (2012): "Testing efficient risk sharing with heterogeneous risk preferences," *American Economic Review*, 102, 428–68.

McMillan, J. and C. Woodruff (1999): "Interfirm relationships and informal credit in Vietnam," *The Quarterly Journal of Economics*, 114, 1285–1320.

Munshi, K. (2011): "Strength in numbers: Networks as a solution to occupational traps," *The Review of Economic Studies*, 78, 1069–1101.

——— (2014): "Community Networks and the Process of Development," *Journal of Economic Perspectives*, 28, 49–76.

——— (2019): "Caste and the Indian Economy," *Journal of Economic Literature*, 57, 781–834.

Munshi, K. and M. Rosenzweig (2006): "Traditional institutions meet the modern world: Caste, gender, and schooling choice in a globalizing economy," *American Economic Review*, 96, 1225–1252.

——— (2016): "Networks and misallocation: Insurance, migration, and the rural-urban wage gap," *American Economic Review*, 106, 46–98.

Nunn, N. (2007): "Relationship-Specificity, Incomplete Contracts and the Pattern of Trade," *Quarterly Journal of Economics*, 122, 569–600, reprinted in D. Bernhofen (ed.), Empirical International Trade, Edward Elgar Publishing, 2010.

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

——— (2001): "Business and Social Networks in International Trade," 39, 1177–1203.

Rauch, J. E. and V. Trindade (2003): "Information, International Substitutability, and Globalization," 93, 775–791.

Singh, K. (1996): *Communities, Segments, Synonyms, Surnames and Titles*, National series, Anthropological Survey of India.

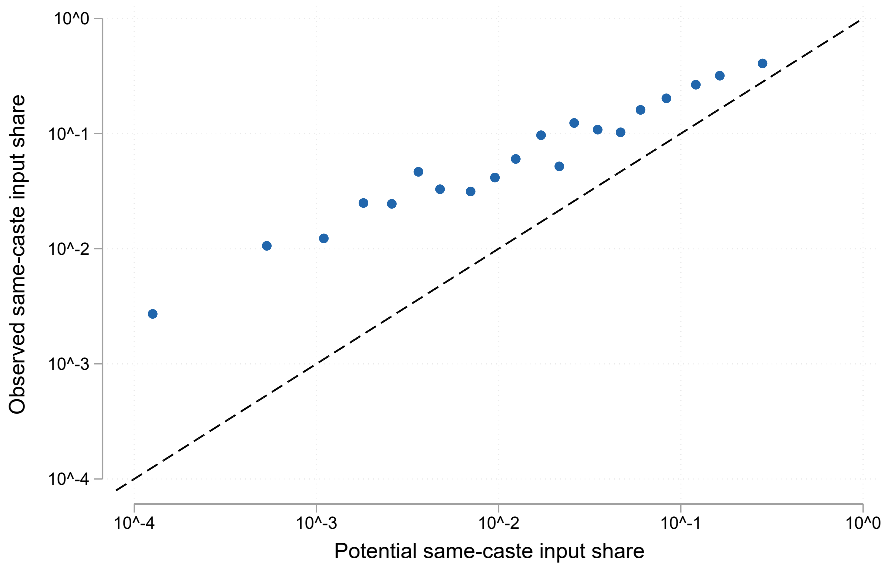
Startz, M. (2021): "The Value of Face-to-Face: Search and Contracting Problems in Nigerian Trade," Tech. rep.

Weber, A. and C. Zulehner (2014): "Competition and gender prejudice: Are discriminatory employers doomed to fail?" *Journal of the European Economic Association*, 12, 492–521.

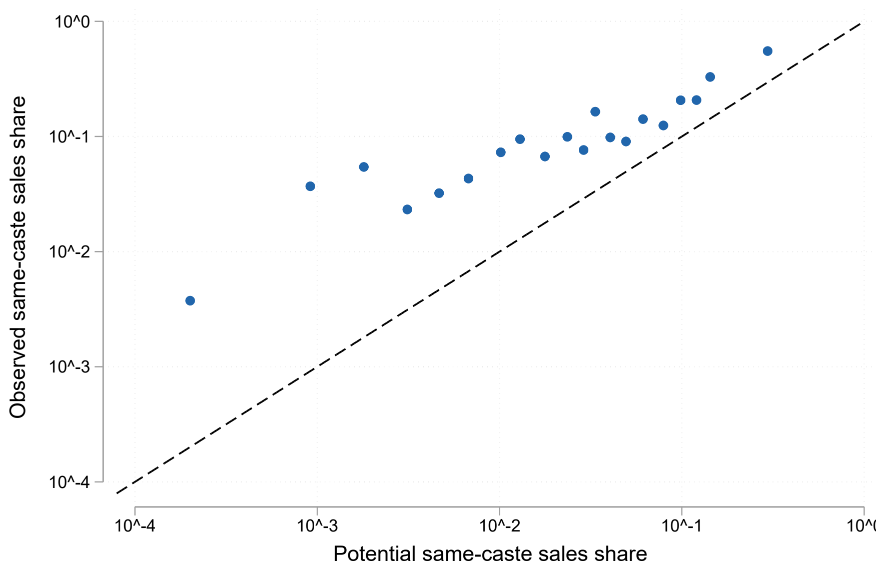
Woodruff, C. (2002): "Non-contractible investments and vertical integration in the Mexican footwear industry," *International Journal of Industrial Organization*, 20, 1197–1224.

Figure 1: Potential and observed same-caste trade

(a) Inputs



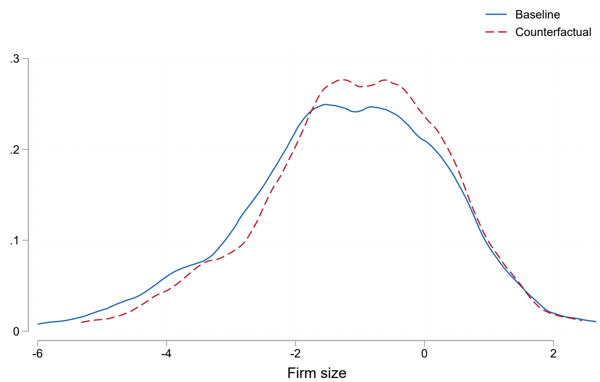
(b) Sales



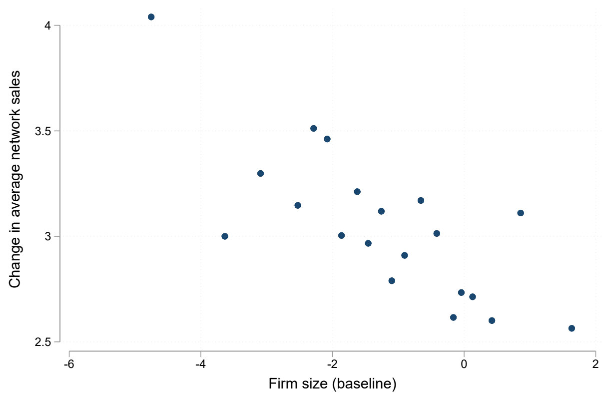
The graphs illustrate the relationship between potential same-caste trade and observed same-caste trade, averaged within 20 vintiles of potential own-caste trade share. A firm's potential same-caste input (sales) share is the share of same-caste suppliers (clients) in all its potential suppliers (clients) in the potential trade sample described in the text, where each supplier (client) 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.

Figure 2: Counterfactual: Caste communities as trade-facilitators

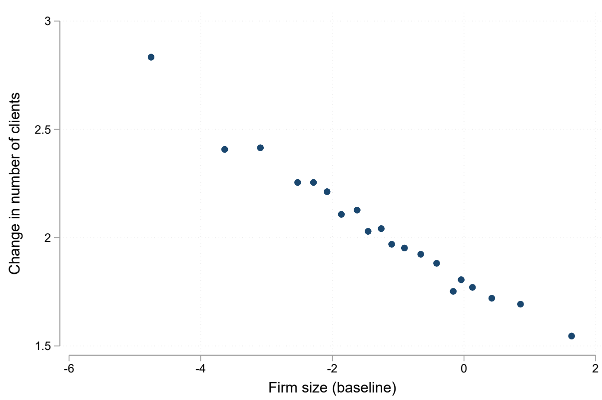
(a) Distribution of firm size



(b) Change in average sales



(c) Change in number of clients



Panel (a) plots the distribution of the firm size, measured by total network sales, of clients per firm in the estimated model ('Baseline') and in a counterfactual scenario ('counterfactual 1' in the main text). The counterfactual assumes all firm-pairs can benefit from the positive effect of castes on trade. Panels (b) and (c) compare the predicted changes in average sales per client (b) and number of clients (c) in our counterfactual scenario compared to the baseline, averaged within 20 vintiles of firm size in the baseline, measured by total network sales.

Table 1: Sample descriptives

	Mean	SD	Median
A: Firms			
Turnover (1000 INR)	21.41	245.52	3.30
Years active	3.95	1.91	4
Is supplier	0.62	0.49	1
Is client	0.92	0.28	1
# Clients	2.98	9.89	1
# Suppliers	3.01	4.06	2
# Potential clients	508.22	795.15	257.67
# Potential suppliers	443.02	461.09	285.67
# Potential same-caste clients	17.74	41.43	1.67
# Potential same-caste suppliers	15.51	30.63	4.33
Observations		106,775	

	Mean	SD	Median
B: Potential trade			
Trade probability (%)	0.72	8.46	0
Transaction amount (1000 INR)	14.93	10780.95	279.38
Same caste probability (%)	3.57	18.55	0
Observations		202,495,680	

Panel A presents firm-level summary statistics. The number of potential suppliers and clients are constructed using the potential trade sample described in the text. 'Years active' is the number of fiscal years in which the firm is observed in our data. 'Is supplier' ('Is client') is an indicator equal to one if a firm is observed at least once selling to (buying from) another firm in our sample. In Panel B each observation is a potential supplier-client pair in a given year, the sample is the potential trade sample described in the text, and the transaction amount is conditional on the pair trading.

Table 2: Caste effects on trade

	(1)	(2)	(3)	(4)
A: Extensive margin				
	$\mathbb{1}(Trade)$	$\mathbb{1}(Trade)$	$\mathbb{1}(Trade)$	$\mathbb{1}(Trade)$
Same caste	1.312 ***	1.003***	1.000***	0.990***
	(0.029)	(0.026)	(0.021)	(0.021)
Obs. (thousand)	202,496	202,496	202,496	202,496
B: Intensive margin				
	Log. trade	Log. trade	Log. trade	Log. trade
Same caste	0.336***	0.332***	0.198***	0.183***
	(0.016)	(0.012)	(0.009)	(0.009)
Obs. (thousand)	1,461	1,461	1,461	1,461
Client location X Supplier location FE		X	X	X
Client X Year FE			X	X
Supplier X Year FE			X	X
Client Product X X Supplier Product FE				X

This table presents results obtained from running specification (1). In Panel A, we use the potential trade sample, described in the text. The outcome variable is an indicator equal to 1 if the two firms are in the same caste, 0 otherwise, and the variable 'same caste' is an indicator equal to 1 divided by the mean probability of trade in the sample (.00726) so that coefficients can be read as the effect of caste on the probability that two firms trade. In Panel B, we use the sample of all observed transactions. The outcome variable is log trade within the pair in the year, 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 onward include fixed effects for each interaction of the location (postcode) of the supplier and the location (postcode) of the client, columns (3) and (4) include supplier $\times$ year and client $\times$ year fixed effects and column (4) includes fixed effects for each interaction of the product sold by the supplier 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 and trade frictions

	(1) $\mathbb{1}(Trade)$	(2) $\mathbb{1}(Trade)$	(3) $\mathbb{1}(Trade)$	(4) Log. trade	(5) Log. trade	(6) Log. trade
Same caste	0.619***	0.739***	0.363***	0.123***	0.116***	0.056*
	(0.048)	(0.067)	(0.080)	(0.025)	(0.021)	(0.031)
Same caste X Court cong.	0.626***		0.629***	0.099**		0.098**
	(0.074)		(0.074)	(0.039)		(0.039)
Same caste X Rel. spec.		0.394***	0.396***		0.104***	0.104***
		(0.095)	(0.095)		(0.029)	(0.029)
Obs. (thousand)	202,496	202,496	202,496	1,461	1,461	1,461

This table presents results obtained from running specification (1) augmented with interaction terms. In columns (1) to (3) the dependent variable is an indicator equal to 1 if the two firms trade in the year and the sample is the potential trade sample defined in the text. In columns (4) to (6) the dependent variable is the log of trade between the two firms in the year and the sample is restricted to all trading pairs. 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 supplier's NIC4 category that are not traded on central exchanges or with a reference price according to Rauch (1999). In columns (1), (2), (3), the variables 'same caste' and all the interaction terms are divided by the mean probability of trade in the sample (.00726). All columns include fixed effects for each interaction of the location (postcode) of the supplier 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 supplier 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: Own-caste preferences and firm exit

	(1) Exit	(2) Exit	(3) Exit	(4) Exit
Own caste share, inputs (demeaned)	0.095*** (0.023)	0.091*** (0.023)	0.083** (0.025)	0.085** (0.031)
Age	-0.081*** (0.002)	-0.087*** (0.002)	-0.086*** (0.002)	-0.086*** (0.003)
Log turnover	-0.275*** (0.005)	-0.282*** (0.005)	-0.315*** (0.007)	
Stratification		Postcode	Product & Postcode	Product & Postcode & Size decile
Observations	364,967	364,967	364,967	364,967

This table presents the coefficients from our Cox model estimating the probability of firm exit, as described in the text. The coefficient 'own-caste share' is the share of input purchased from firms from the client's caste in a given year, demeaned by the industry average. Firm age is the time in years since registration. Stratification lists the variables that define the subgroups for comparison, i.e., subgroup-specific baseline. Standard errors are clustered at the Postcode X product level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 5: Estimation results: parameter estimates and model fit

	Data	Baseline	No matching cost	No contract. premium
	(1)	(2)	(3)	(4)
Estimated Parameters				
μ_{lnF}		17.457	17.373	17.435
σ_z		0.145	0.013	0.167
σ_F		4.138	3.980	4.168
ρ =corr (z, F)		0.176	-0.995	0.219
$1/\delta_z$ (rel contracting premium)		0.968	0.896	
δ_f (caste matching cost)		-2.606		-2.713
Targeted moments				
var(sales)	2.38	2.380	2.377	2.382
var(ln n clients)	2.200	2.200	2.150	2.198
mean(ln n clients)	-4.550	-4.500	-4.482	-4.500
Market sh & n clients corr.	0.010	0.010	0.065	-0.004
Intensive margin effect	0.122	0.122	0.326	0.027
Extensive margin effect	0.660	0.660	-0.142	0.663
Untargeted moments				
ln n caste clients	-2.510	-3.624	-4.376	-3.621
Neg degree assortativity	-0.4673	-0.284	-0.257	-0.283

This table presents the results from the SMM estimation. The firms panel reports the values of the estimated parameters. The second and third panels report the values of targeted and untargeted moments. Sales are demeaned, Log number of clients ('ln n clients') is normalised by the total number of firms. 'RF coeff on sales' stands for the coefficient on the *same caste* dummy variable estimated in equation 1 using log sales as the dependent variable, while 'RF coeff on trade prob' stands for the coefficient on the *same caste* dummy variable estimated in equation 1 using a *Trade* dummy to measure the probability of trading. Both coefficients are scaled down to 0.6 to account only for the effect of castes in the presence of high contractual frictions. 'ln n caste clients' is the number of same caste clients normalised by the potential number of same caste clients for each firm. 'Neg degree assortativity' is the slope of regressing the average connectivity of a firm's clients (number of suppliers of each clients), over the number of clients (as reported in Figure A9). Column 2 reports the results from the baseline model while column 3 reports the results from a restricted model with only an intensive margin caste parameter (the contracting-premium effect), while column 4 reports the results from a restricted model with only the extensive margin parameter (matching cost effect).

Table 6: Aggregate effects of Community networks: counterfactual exercises

A: Counterfactuals	C1	C2
Welfare change	1.357	0.988
Change in total number of connections	1.710	0.975
Change in average network sales	1.212	0.980
Change in average input price	0.859	1.005

B: Counterfactual 1 decomposition	Matching cost effect	Contracting premium effect
Welfare change	1.2949	1.0362
Change in total number of connections	1.710	0.975
Change in average network sales	1.212	0.980
Change in average input price	0.881	0.984

This table presents the results from the counterfactual exercises. Panel A reports the results from our two main counterfactuals. C1 reports the results from a counterfactual exercise in which we extend the positive effect of caste on trade to all potential supplier-client pairs. C2 reports the results from the second counterfactual in which we remove all the positive effects of castes on trade, both the lower relative contracting premium and the lower matching costs. Panel B presents the results from decomposing counterfactual C1 into the effect of the matching cost parameter and the effect of the different contracting premium. Column 1 in panel B presents the counterfactual outcomes of extending only the extensive margin caste benefit: all supplier-client pairs enjoy the lowest matching costs that we observe within communities, while the pair-productivity effect is removed. Column 2 in panel B reports the outcomes of extending only the intensive margin caste benefit: all supplier-client pairs enjoy the higher pair-productivity that we observe within communities, while the matching cost effect is removed: all supplier-client pairs enjoy the higher profitability of same-caste pairs, but the matching cost is differences are removed.

Appendix (for online publication only)

A Data construction

We use the data by Cassan et al. (2021) based on the data collected by Singh (1996), which lists 2,205 castes (or 'main communities') and information on the names of their various associated subgroups, synonyms, surnames, and the respective sources or origin. In our illustrative example in Figure A5 the castes is Gareri. We construct a list of all names and their associated castes. Since a name can be listed for more than one caste, we often find multiple castes for a given name and order them alphabetically. In our assignment, we only keep the most relevant matches by origin and type. In step 1, we only match castes to names which are listed as surnames with origin West Bengal (from the example Figure A5, the name Bhagat would be matched with the caste Gareri). In step 2, we match all remaining unmatched names to castes based on other group names from West Bengal (e.g., we would match the caste Gareri to the name Goneri *if* we could not find another caste in step 1). We repeat this procedure twice more, matching unmatched names using all surnames from other origins (step 3), and using all other group names from other sources (step 4).

We match the names on our list to the names in the VAT records; 82% of firms have a name recorded in the original data set. We perform fuzzy string matching to account for different spellings and manually verify every match, which accounts for 8% of our matches. Overall, we find a caste for 91 % of firms with a name in the VAT data [21], or 75% of all firms. From this sample, we are pruning based on the trade network and only keep firms which are trading with at least one firm with an assigned caste, dropping an additional 19% of firms.

In our final data, we assign 66 % of firms to castes based on surnames with origin West Bengal and 20% based on surnames from other states[22]. 65% of firms have more than one caste assigned to them, 40% have five or more. We perform multiple robustness checks on caste matching: first using only the matches based on West Bengali surnames and second, if available, using the second assigned caste in alphabetical order. Third, we use the full sets of castes to compute the

[21] including firm names or other non-surnames

[22] We furthermore assign 6% based on other group names from West Bengal, and 8% based on group names from other states

Jaccard similarity coefficient between both firms' associated castes, which is the size of the intersection divided by the size the union. We thus obtain a measure between 0 (two firms have none of their assigned castes in common) and 1 (all castes are the same), similar to the original indicator. The results of these robustness checks are in Tables A1 and A2.

Considering the distribution of firms in our final sample across size bins, districts, and sectors, we find that it does not seem to differ substantially in observables from the universe of firms in the VAT data: we lose proportionally more firms at the extreme ends of the size distribution, mostly very small firms, and we see very little systematic deviation in the geographic and sectoral distribution (Table A7).

B Features of the firm network in West Bengal

In section 4 we use a theoretical framework of supplier-client networks with two-sided firm heterogeneity and endogenous match formation, built on Bernard et al. (2022) to examine the aggregate effects of caste affiliation on trade. The application of their framework to our context is motivated by three empirical patterns in our data.

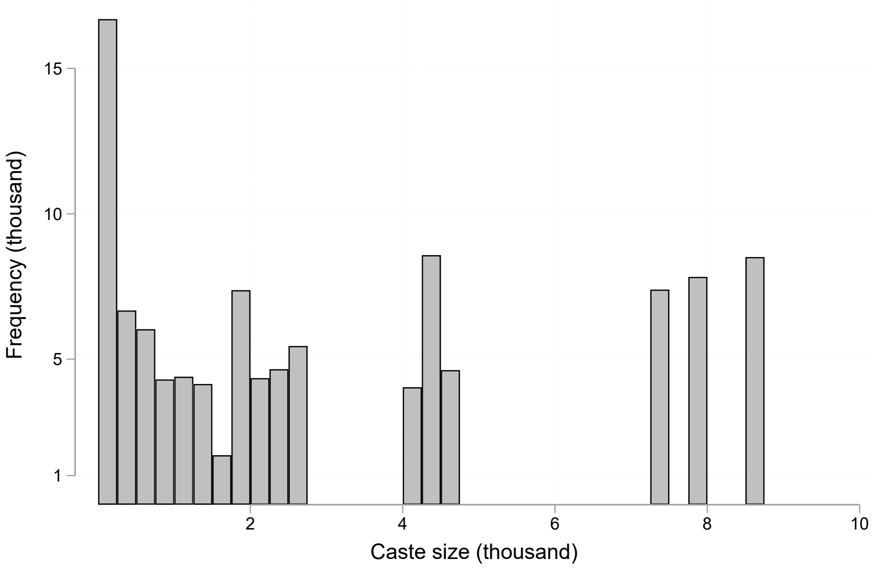
Fact 1: The distributions of firm sales and supplier-client links are highly dispersed. The distributions of firm size (total sales), number of suppliers and number of clients have a high dispersion, spanning several orders of magnitude (see Figure A6). The largest firms sell thousands of times more than the average firm and have thirty to fifty times more suppliers or clients. This high dispersion in the distribution of sales and links suggests that firm heterogeneity is high in West Bengal, calling for a model which accounts for this heterogeneity.

Fact 2: Firms with more clients have higher sales and higher sales per client, but not higher market shares. We find that large firms have more clients and also higher sales per client (see Figure A7). This pattern suggests that firm size affects both the ability to adopt more clients, and the ability to sell more to those clients. However, this strong positive relation is weaker when we look at the average market share of a firm over its clients, plotted against the number of clients (see Figure A8). This suggests that another source of firm heterogeneity in addition to firm productivity is at play, as highlighted by Bernard et al. (2022) in the context of Belgium. The slope of this last figure will help us estimate the correlation between firm productivity and firm relationship capability in the model.

Fact 3: Suppliers with more clients match with clients who have fewer suppliers on average. Our data features negative degree assortativity: firms with fewer customers match with well connected clients, while firms with many customers match with less-well connected firms on average (see Figure A9). This motivates the choice of a parsimonious model of firm matching where a match is formed when the profits of the match are larger than the cost of the match.

C Additional Figures and Tables

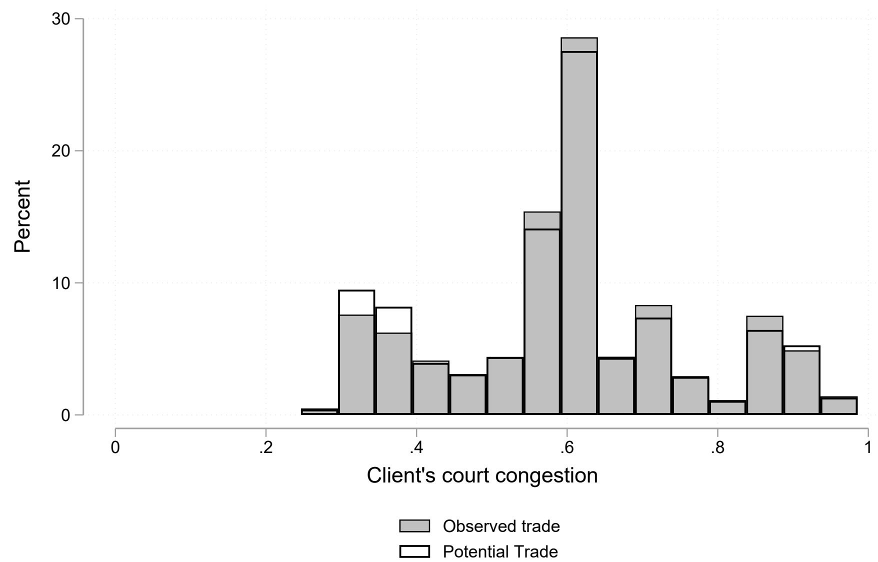
Figure A1: Distribution of caste sizes



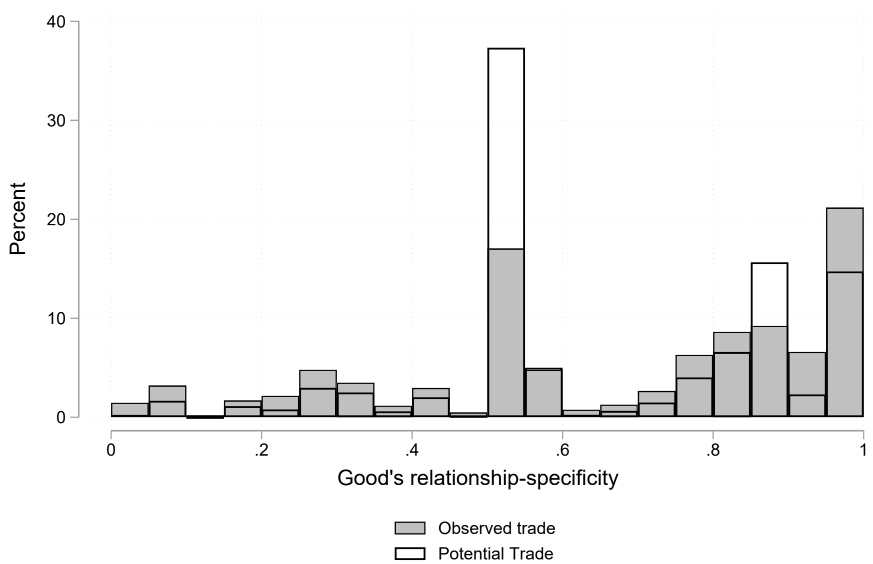
This graph plots the size distribution of every firm's assigned caste. Size refers the total number of firms in our sample which are assigned to a given caste. Bars can represent more than one caste.

Figure A2: Distribution of our proxy variables for contractual frictions

(a) Court congestion



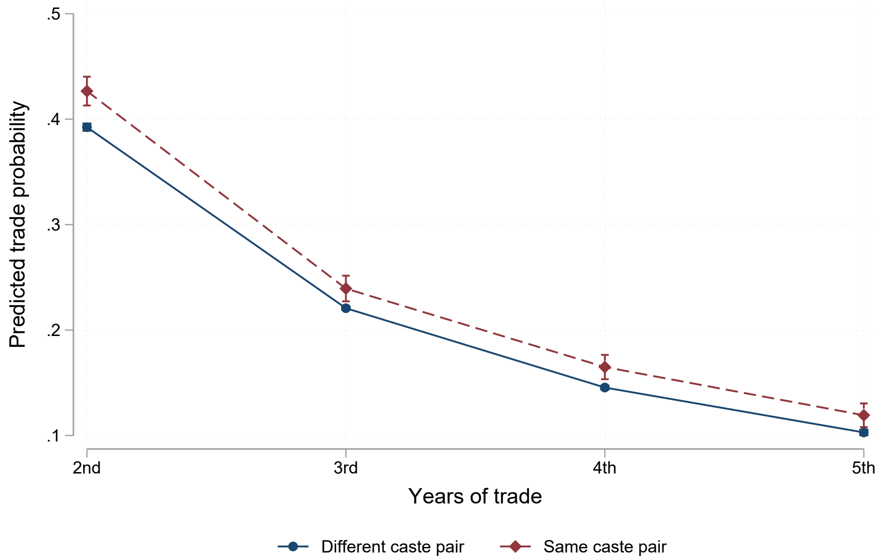
(b) Product relationship-specificity



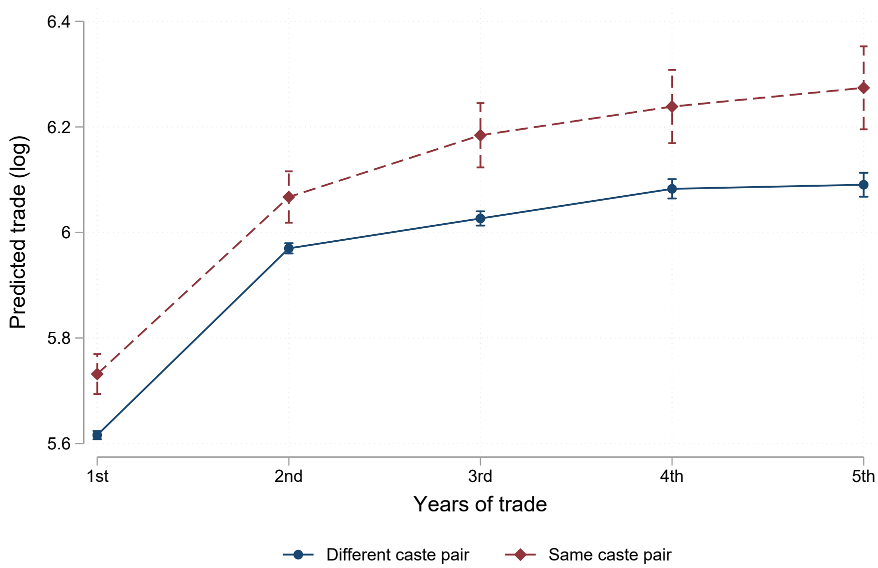
This graph illustrates the distribution of the trade friction variables which are used in Section 3.2 and described in Section 2.3. Panel (a) plots the distribution of the court congestion variable for all pairs in our observed (potential) trade sample on the (potential) client's side. The mean (SD) is .61 (.16) in the observed trade sample and .60 (.16) in the potential trade sample. Panel (b) plots the distribution of relationship-specificity of the (potential) supplier's good for all pairs in our observed (potential) trade sample. The mean (SD) is .67 (.28) in the observed trade sample and .65 (.23) in the potential trade sample.

Figure A3: Predicted trade, new pairs 2011-2012

(a) Predicted trade probability



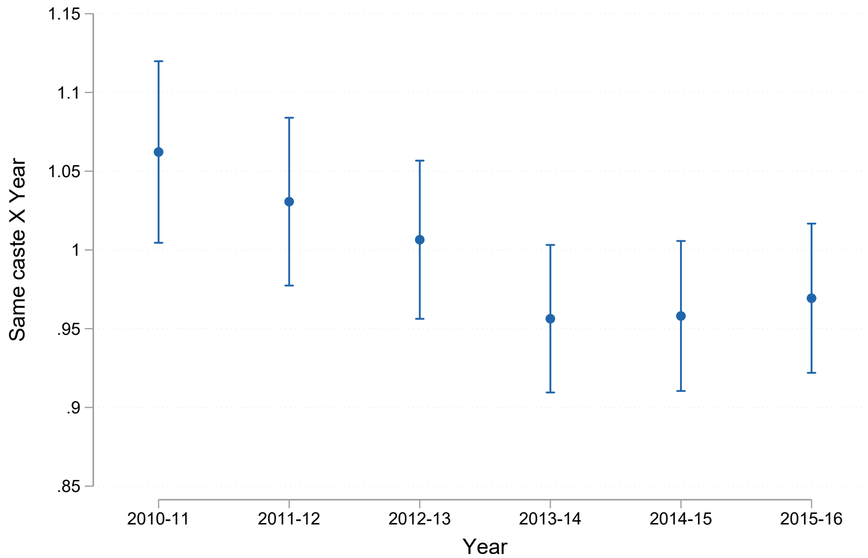
(b) Predicted trade volume (conditional)



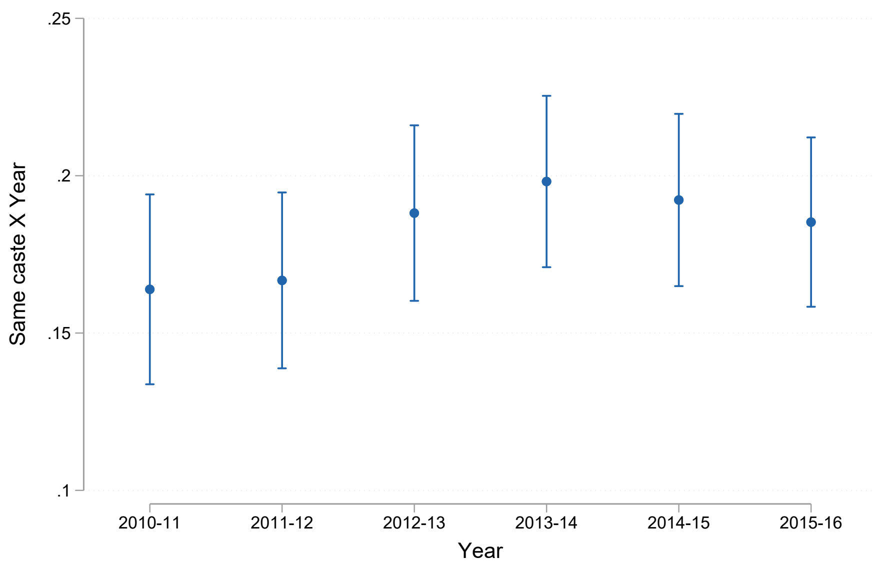
These graphs plot the trade dynamics for newly formed trade relationships separately for same-caste relationships and across-caste relationships. Each point represents a predicted outcome, computed separately for pairs for which both firm owners belong to the same caste and for other pairs, with 95% 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 supplier are present in the data in all subsequent years. 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: $Y_{ijt} = \sum_k \beta^k \mathbb{1}(c_i = c_j) \times \mathbb{1}(Year\_trade = k) + \sum \theta^k \mathbb{1}(Year\_trade = k) + \gamma X_{ijt} + \mu_i + \mu_j + \epsilon_{ijt}$. 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. All specifications include fixed effects for each interaction of the location (postcode) of the supplier and the location (postcode) of the client, supplier $\times$ year and client $\times$ year fixed effects and fixed effects for each interaction of the product sold by the supplier and the product sold by the client, following the specification used in column (4) of Table 2. Indicated confidence intervals are 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 A4: Same caste coefficient over time

(a) Extensive margin



(b) Intensive margin



These graphs plot present results obtained from running specification (1) augmented with interaction terms for each year in our data. I.e., for the set of all fiscal years in our data k, we run $Y_{ijt} = \sum_k \beta^k \mathbb{1}(c_i = c_j) \times \mathbb{1}(Year = k) + \sum \theta^k \mathbb{1}(Year = k) + \gamma X_{ijt} + \mu_i + \mu_j + \epsilon_{ijt}$. In panel (a) the dependent variable is an indicator equal to 1 if the two firms trade in the year and the sample is the potential trade sample defined above. In panel (b), the dependent variable is the log of trade between the two firms in the year and the sample is restricted to all trading pairs. The variable 'same caste' is an indicator equal to 1 if the two firms are in the same caste, 0 otherwise. In panel (a), all interaction terms with the variable 'same caste' are divided by the mean probability of trade in the sample (.00726). AAll specifications include fixed effects for each interaction of the location (postcode) of the supplier and the location (postcode) of the client, supplier $\times$ year and client $\times$ year fixed effects and fixed effects for each interaction of the product sold by the supplier and the product sold by the client, following the specification used in column (4) of Table 2. Indicated confidence intervals are at the 95% level, standard errors clustered two-way at the level of the supplier and the client in parentheses. Sample size: (a) N=202,495,680 (b) N=1,461,018.

Figure A5: Example entry for the caste 'Gareri' from Singh (1996)

GARERI

Synonyms: Bherihar, Pal [Bihar]
Goneri, Gonrhi [West Bengal]

Groups/subgroups: Dhengar, Gangojoli, Nikhar, Phurukbadi [Bihar]
Dhangarh, Nikhar [West Bengal]

* *Subcastes:* Dhengar, Farakhabadi, Gangajali, Nikhar [H.H. Risley]

Titles: Kamblia, Kammali, Marar, Ratu [H.H. Risley]

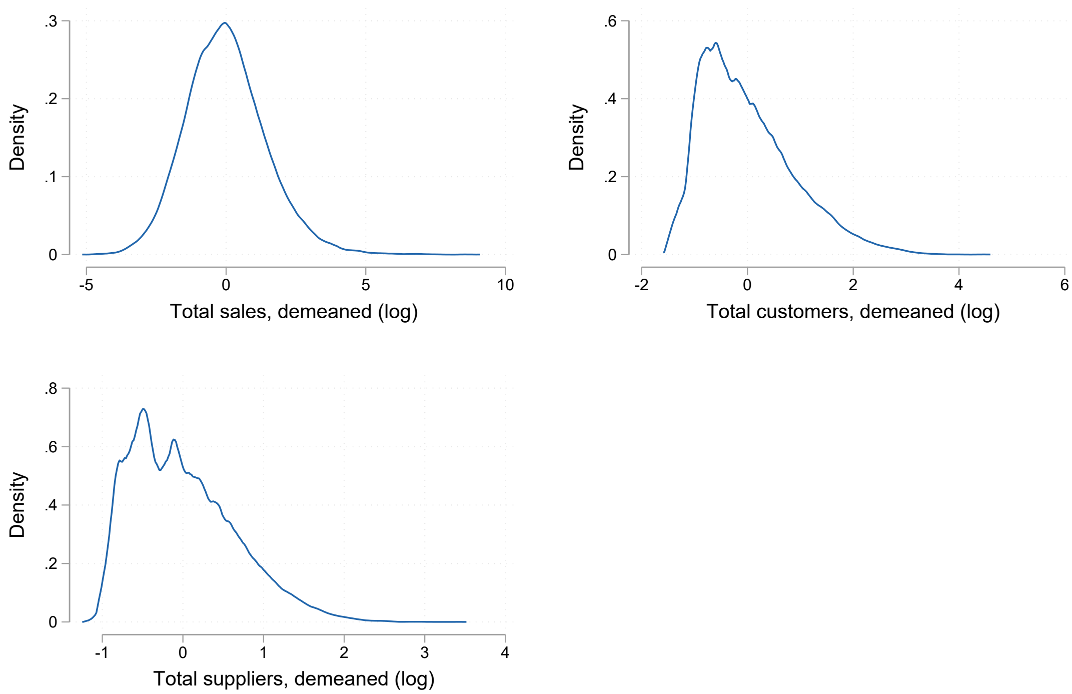
Surnames: Bhagat, Chowdhury, Mandal, Pal [Bihar]
Bhagat, Choudhury, Ghosh, Pal [West Bengal]

Exogamous units/clans: Ahir, Bandharia, Chowharia, Khandel [West Bengal]

Exogamous units/clans (gotra): Ahir, Basdharia, Bilar, Chandel, Chaurasia, Nakwar [Bihar]

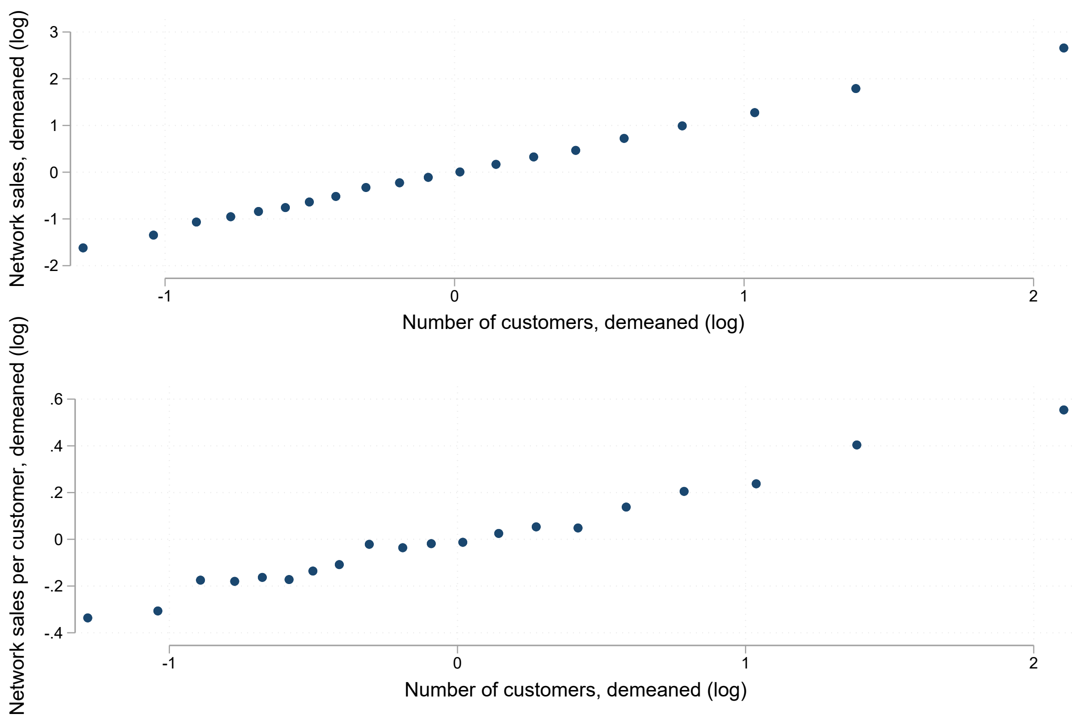
Exogamous units/lineages: Ahir, Bandharia, Chowharia, Khandel [West Bengal]

Figure A6: Distribution of firm sales, number of clients and number of suppliers.



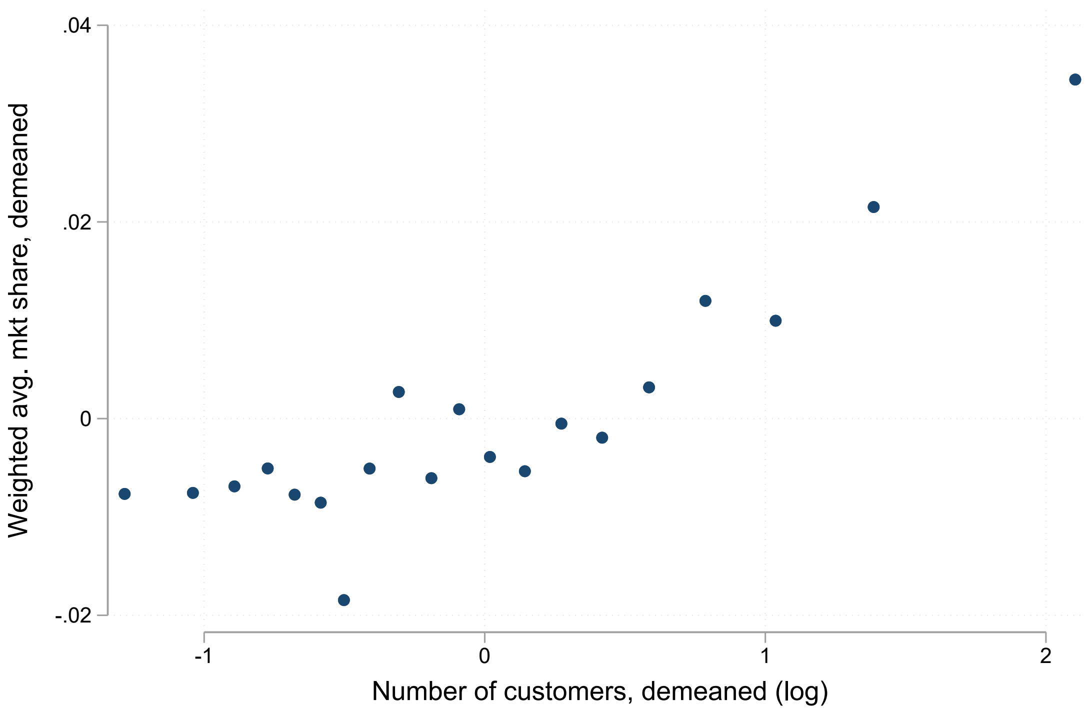
The graph illustrates the density of network sales, total clients and total suppliers in the firms in our dataset.

Figure A7: Total Network Sales, Average Sales and Number of clients



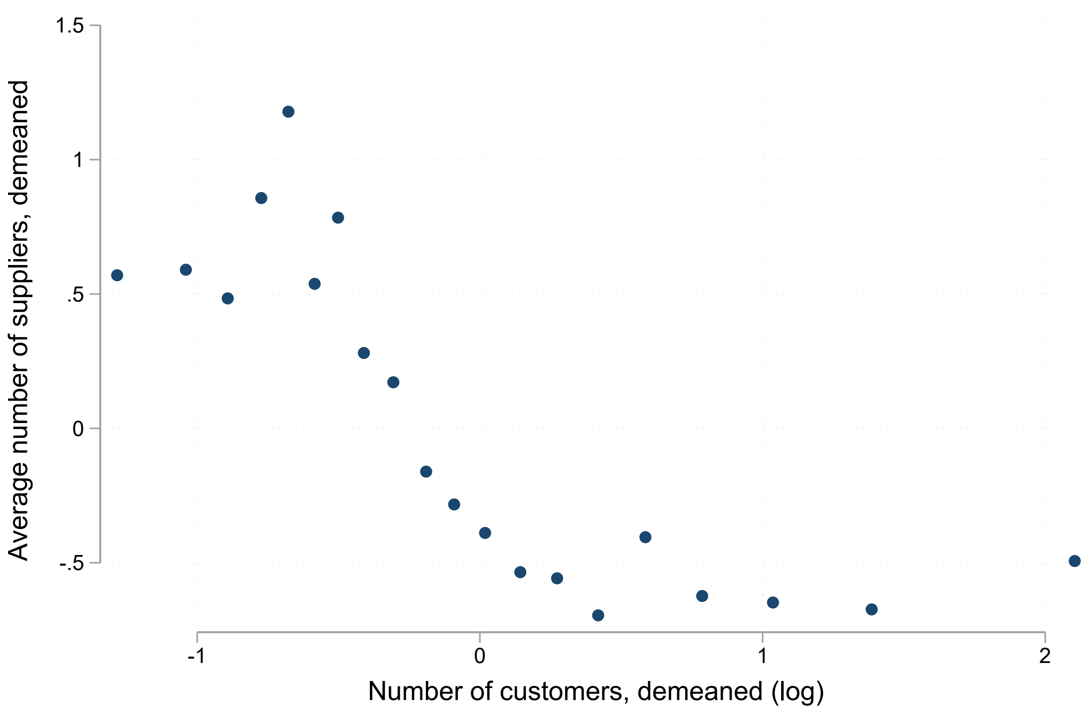
The binned scatterplots group firms into 20 equal-sized bins by number of clients (log), and compute the mean of the variables on the x- and y-axes in each bin. Network sales are firm's total sales to customers in the domestic production network. All variables are demeaned by 4-digit industry averages.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

Figure A8: Average market share and number of clients



The binned scatterplot groups firms into 20 equal-sized bins by number of clients (log), and computes the mean of the variables on the x and y-axes in each bin. Average market share is the geometric mean of the market share for supplier *i* across its clients. All variables are demeaned by 4-digit industry averages.

Figure A9: Degree Assortativity



The binned scatterplot groups firms into 20 equal-sized bins by number of clients (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 clients of firm i. All variables are demeaned by 4-digit industry averages.

Table A1: Robustness, Extensive margin

	2011 - 2016									2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$\mathbb{1}(Trade)$	$\mathbb{1}(Trade)$	$\mathbb{1}(Trade)$	$\mathbb{1}(Trade)$	$\mathbb{1}(Trade)$	$\mathbb{1}(Trade)$	$\mathbb{1}(Trade)$	$\mathbb{1}(Trade)$	$\mathbb{1}(Trade)$	$\mathbb{1}(Trade)$	$\mathbb{1}(Trade)$	$\mathbb{1}(Trade)$
Same caste	0.990***	1.004***	1.046***	1.351***	0.936***	0.996***	1.355***	1.050***	0.990***	1.003***	1.050***	1.420***
	(0.021)	(0.025)	(0.024)	(0.028)	(0.025)	(0.022)	(0.031)	(0.022)	(0.110)	(0.025)	(0.027)	(0.036)
Robustness	Main	4-digit NIC	2nd caste	All castes	West Bengali sur-names	No Muslim castes	No large castes	No small castes	Product & Post Code clus-tered SEs	Main	All po-tential sellers	Recipe
Obs. (thousand)	202,496	116,756	202,496	202,496	96,664	165,621	119,417	175,288	202,496	33,665	133,804	169,859

This table presents results obtained from running specification (1), described in the text, on different samples of our data as described below. In columns (1)-(3) and (5)-(12),, the variable 'same caste' is an indicator equal to 1 divided by the mean probability of trade in the respective sample if the two firms are in the same caste, 0 otherwise. Column (1) presents the results from our main specification as shown in Table 2. 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) uses the full sets of castes associated with the two firms and 'same caste' is the Jaccard similarity coefficient, as described in Appendix A. Column (5) restricts the sample to firms which have a name that explicitly connected to West Bengal in the original source. Column (6) excludes all pairs in which at least on of the firms owners' last name is categorized as Muslim in the original source. Column (7) excludes all firms from one of the 3 largest castes (Aguri, Baidya, Marwari). Column (8) excludes firms who have no potential trading partner from their own caste in the sample. Column (9) is based on the main sample, but uses two way-clustered standard errors by Client location and industry.
Columns (10) - (12) use only data from the year 2013: Column (10) uses the main sample described in the text. Column (11) uses the same procedure to identify potential suppliers, but uses the full set of potential trading partners. Column (12) 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 supplier 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 supplier 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 A2: Robustness, Intensive margin

	(1) Log. trade	(2) Log. trade	(3) Log. trade	(4) Log. trade	(5) Log. trade	(6) Log. trade	(7) Log. trade	(8) Log. trade	(9) Log. trade
Same caste	0.183^{***}	0.195^{***}	0.188^{***}	0.215^{***}	0.139^{***}	0.185^{***}	0.248^{***}	0.180^{***}	0.183^{***}
	(0.009)	(0.011)	(0.009)	(0.010)	(0.012)	(0.009)	(0.013)	(0.009)	(0.023)
Robustness	Main	4-digit NIC	2nd caste	All castes	West Bengali castes	No Muslim castes	No large castes	No small castes	Product & Post Code clustered SEs
Obs. (thousand)	1,461	885	1,461	1,461	620	1,205	866	1,196	1,461

This table presents results obtained from running specification (1), described in the text, on different samples of our data as described below. In columns (1)-(3) and (5)-(9), the variable ‘same caste’ is an indicator equal to 1 if the two firms are in the same caste, 0 otherwise. Column (1) presents the results from our main specification as shown in Table 2. 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) uses the full sets of castes associated with the two firms and ‘same caste’ is the Jaccard similarity coefficient, as described in Appendix A. Column (5) restricts the sample to firms which have a name that explicitly connected to West Bengal in the original source. Column (6) excludes all pairs in which at least on of the firms owners’ last name is categorized as Muslim in the original source. Column (7) excludes all firms from one of the 3 largest castes (Aguri, Baidya, Marwari). Column (8) excludes firms who have no potential trading partner from their own caste in the sample. Column (9) 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 supplier and the location (postcode) of the client, supplier $\times$ year and client $\times$ year fixed effects and fixed effects for each interaction of the product sold by the supplier 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: Varna and caste

	(1) $\mathbb{1}(Trade)$	(2) $\mathbb{1}(Trade)$	(3) $\mathbb{1}(Trade)$	(4) Log. trade	(5) Log. trade	(6) Log. trade
Same castegroup	0.126***		0.064***	0.037***		0.014***
	(0.005)		(0.005)	(0.005)		(0.005)
Same caste		0.990***	0.967***		0.183***	0.179***
		(0.021)	(0.021)		(0.009)	(0.009)
Obs. (thousand)	202,496	202,496	202,496	1,461	1,461	1,461

This table presents results on larger caste groups' (varnas) effect on trade, running a regression based on our main specification (1). The variable 'same caste' is an indicator equal to 1 if the two firms are in the same caste, 0 otherwise; the variable 'same caste group' is one if the two firms belong to the same caste group (SC, ST, OBC, non-scheduled) as outlined by the "West Bengal Scheduled Castes, Scheduled Tribes and Other Backward Classes Development Finance Corporation". In columns (1), (2), (3), the variables 'same caste' and 'same caste group' are divided by the mean probability of trade in the sample (.00726) 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: Caste effect on firm exit, sellers

	(1) Exit	(2) Exit	(3) Exit	(4) Exit
Own caste share (demeaned)	0.142*** (0.022)	0.123*** (0.021)	0.124*** (0.026)	0.202*** (0.035)
Age	-0.091*** (0.002)	-0.089*** (0.002)	-0.087*** (0.003)	-0.085*** (0.004)
Log sales	-0.263*** (0.006)	-0.284*** (0.005)	-0.342*** (0.007)	
Stratification		Postcode	Product & Postcode	Product & Postcode & Size decile
Observations	227,716	227,716	227,716	227,716

This table presents the untransformed coefficients from our Cox model estimating the probability of firm exit, as described in the text. The coefficient 'own-caste share' is the share of sales going to firms from the supplier's caste in a given year, compared to the industry average. Firm age is the time in years since registration. Stratification lists the variables that define the subgroups for comparison, i.e. subgroup-specific baseline. Standard errors are clustered at the Postcode X good level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table A5: Caste effect and firm age

	(1) $\mathbb{1}(Trade)$	(2) $\mathbb{1}(Trade)$	(3) $\mathbb{1}(Trade)$	(4) Log. trade	(5) Log. trade	(6) Log. trade
Same caste	0.990***	0.978***	0.960***	0.183***	0.184***	0.185***
	(0.021)	(0.021)	(0.022)	(0.010)	(0.010)	(0.010)
Same caste × Experienced client		0.028			-0.002	
		(0.022)			(0.012)	
Same caste × Experienced supplier			0.069**			-0.003
			(0.027)			(0.013)
Obs. (thousand)	202,496	202,496	202,496	1,461	1,461	1,461

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 'experienced supplier' and 'experienced client' are indicators whether the (potential) supplier, respectively client, were registered in 2005 or earlier. In columns (1), (2), (3), the variables 'same caste' and all of its interaction terms are divided by the mean probability of trade in the sample (.00726) All columns include fixed effects for each interaction of the location (postcode) of the supplier 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 supplier 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 A6: Externally calibrated parameters

Parameter	Definition	Value	Source
α	Labor cost share	0.4	Boehm and Oberfield (2020)
μ	Markup	1.34	De Loecker et al. (2016)
X	Aggregate final demand	1	Normalization
σ_{ε}	Pair matching cost dispersion	7	Bernard et al. (2022)
mean $\mathcal{C}$	Share of same-caste pairs	3.4%	Calibrated

Table A7: Final sample after cleaning

	VAT data	Final sample
Turnover (INR):		
$\leq$ 500	16.71	10.82
500.1 - 1000	11.40	11.18
1,000.1 - 5,000	35.29	39.66
5000.1 - 10,000	12.05	13.87
10,000.1-100,000	20.21	21.46
$>$ 100,000	4.34	3.02
District:		
Bankura	1.44	1.34
Bardhaman	6.31	6.41
Birbhum	2.14	1.98
Coochbehar	1.40	1.41
Dakshin Dinajpur	0.55	0.53
Darjeeling	4.04	4.67
Hoogly	4.52	4.72
Howrah	11.54	13.89
Jalpaiguri	2.42	2.46
Kolkata	42.63	39.64
Malda	1.36	1.36
Medinipur (E)	2.59	2.37
Medinipur (W)	2.43	2.37
Murshidabad	2.24	1.96
Nadia	2.63	2.62
North 24 Parganas	5.69	6.00
Others	0.02	0.02
Purulia	1.14	1.07
South 24 Parganas	3.96	4.17
Uttar Dinajpur	0.95	1.01
Sector:		
Chemical products (incl. pharma)	8.41	7.88
Construction materials	14.14	13.97
Electrical & electronic goods	12.30	13.63
Food, drink & tobacco	11.74	10.27
Household goods	2.68	2.69
Machines & equipment	14.88	15.92
Metals	7.84	8.80
Mining & energy	2.20	1.99
Other	6.62	6.57
Rubber & plastic	3.53	3.76
Textiles	8.70	7.60
Wood & paper	6.96	6.92
Observations	177,973	106,775

This table presents the distribution of firms in percentage by size categories, districts, and sectors for both the universe of firms in the VAT data ('VAT data') and the sample of firms after assigning castes based on surnames and pruning the network, as described in the text ('Cleaned sample').