Firm-to-Firm Referrals*

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Abstract

We make randomized firm-to-firm referrals between 700 supplier and client firms in the industry producing the Chinese writing brush. Subsidized referrals lead to subsequent transactions and a partial crowding out of prior partners; information-only referrals have no effect. The referrals increase revenue, profit, and hours worked in supplier firms and growth-oriented client firms. Treated suppliers increase product quality, while treated clients expand product variety into higher-quality products, suggesting that the referrals enable complementary upgrading. Treated firms increase beliefs about the value of partners, search for partners, and the number of non-referred partners, suggesting that pessimistic beliefs is a key partnering friction. The referrals generate very large private and social returns.

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Suppliers and clients are essential for industrial firms, but frictions in firm-to-firm access may prevent the efficient formation of supplier-client links. Search frictions may prevent firms from finding partners, and matching frictions may prevent partnerships after a candidate partner is found. As a result, firms may end up with too few partners or the wrong set of partners, constraining business performance and industrial upgrading. Despite the potential importance of these forces, the evidence on firm-to-firm access is thin. Recent work has evaluated interventions that create firm-to-firm connections as a byproduct of infrastructure developments such as mobile phone networks or speed trains (Jensen and Miller 2018, Bernard, Moxnes and Saito 2019); or that create cross-country connections (Atkin, Khandelwal and Osman 2017a). But we lack evidence on interventions that directly target creating connections among firms that are spatially close. The evidence is also thin about the mechanisms through which improving firm-to-firm access shapes industry outcomes, such as by changing the structure of the network and by generating industrial upgrading, and about the overall welfare impacts of these changes. Finally, we lack evidence on the nature of frictions that prevent firms close to each other from forming productive partnerships.

To make progress on these issues, we conducted a field experiment in China, with firms in the same county and industry, in which we evaluated the impact of firm-to-firm referrals. We used self-collected survey data on both firm characteristics and firm networks to construct referrals, and created randomized variation both at the level of links and at the level of firms. We find that the referrals rewired the network, greatly improved business performance, increased product quality among supplier firms, and expanded product variety among client firms. Despite the large gains we estimate, firms did not partner more on their own because they undervalued the benefit from new partners. We estimate that the social return from our intervention was 1,350% per year, highlighting the importance of firm-to-firm access for economic development.

In Section 1 we present our context and experimental design. We work with the industry producing the Chinese brush pen, a culturally important product that remains popular today, in the county that is the globally leading location of production. Based on their main production activity, firms in the industry can be classified into two main layers in the supply chain. Input suppliers (suppliers) produce the brush head and the handle; and final good producers (clients) assemble these inputs and sell the final good. This setting is ideal for our purposes. The industry is spatially concentrated so that search frictions are probably lower than in other contexts; the supply chain is simple; and product variety and quality, two key dimensions of upgrading, are measurable by us and by industry experts. Our sample of 700 firms covers the vast majority of firms in the local industry. We surveyed these firms five times between 2018 and 2023, and in each survey we collected information on both business performance and the firm-to-firm transaction network.

In 2021 we introduced our referral intervention. We constructed referrals between supplier and client firms using the prior data, aiming to find firm pairs that would be good matches. We created two types of link-level variation in referrals. (1) *Unscreened versus screened* referrals differed in the data requirements. We constructed screened referrals using the full network data, based on the idea that a firm pair may be a good match if the supplier has close competitors already selling to the client, or the client has close competitors already buying from the supplier. We constructed unscreened referrals using only the firm data, ensuring a basic product type match between the supplier and the client. (2) *Information versus subsidized* referrals differed in how we introduced the firms. For information referrals we provided the contact details of the candidate partner and informed the firm that the researchers—working in collaboration with the local government—find this candidate partner a good potential match. For subsidized referrals, we in addition offered the client firm a 50% discount for a first transaction within a two-month period, up to a cap.

We randomized all suppliers, and all clients, into two equal-sized groups: T1 and T0. In effect, T1 will be our treatment arm and T0 our control arm at the firm level. We constructed a set of candidate referrals between T1 suppliers and T1 clients, and another set between T0 suppliers and T0 clients. For each client firm, we constructed three referrals, two screened and one unscreened.[1] We made all the candidate referrals between T1 suppliers and T1 clients; all of these were subsidized referrals. We made a quarter of the candidate referrals between T0 suppliers and T0 clients; these were information-only referrals. We did not make the remaining T0-to-T0 candidate referrals. Thus, T0 is a union of the information treatment and the control group. The reason for this design is that based on a pilot we expected the information treatment to have no effect on transactions,

[1] To ensure that all supplier firms get some and no supplier firms get too many referrals, we used a matching algorithm which was based on finding the minimum-cost flow in a directed network (Edmonds and Karp 1972).

which was subsequently confirmed in the data. Thus, we can think of T0 as a counterfactual for T1, and we will sometimes refer to firms in T1 as treated and firms in T0 as untreated.

We measure take-up of the subsidized referral with the firms showing proof of the transaction and taking the subsidy. Take-up was high: about 60% of T1 firms took up at least one subsidized referral, and about 48% of subsidized referrals were taken up.

In Section 2 we study the impact of referrals on the business network. We begin with link creation, measured with transactions between referred partners after the subsidy period ended. The screened subsidy, relative to the unmade control referrals, increased the probability of subsequent transactions by 45 percentage points, and significantly increased the number and value of transactions. The unscreened subsidy significantly increased these measures though with point estimates about half as large. These results document the importance of partnering frictions: despite the firms being in the same location and having been active in the industry for over 20 years, our referrals created many new partnerships. In contrast to the subsidized referrals, the information referrals had small and insignificant effects on transactions. This result points specifically at a matching friction which prevents firms from transacting even when a partner is identified. We also find that the subsidized referrals increased firms' (expected or actual) satisfaction with the candidate partner, implying that firms undervalued benefits of the referrals. This undervaluation may help explain why the information referrals did not generate transactions.

By creating new links, the referrals could crowd out existing links. We find that treating one of the firms in a pre-existing link reduces the probability that the link remains by about 20 percentage points, and reduces the number of transactions and the transaction value as well. Thus, the referrals generated business stealing in the network. Firms were more likely to keep partners they were more satisfied with, suggesting that business stealing may reflect a reallocation to better partners.

In Section 3 we explore whether the referrals affected firm performance. We begin by comparing treated (T1) and untreated (T0) firms. Among suppliers, we find significant and large gains in several key measures of firm performance: revenue, profit, hours worked, number of clients, and satisfaction with clients. For example, we estimate revenue gains of 24 log points. Among clients, we find significant gains in the number of suppliers and satisfaction with suppliers, but not in the other outcomes. We then zoom in on a subsample of client firms where we expect impacts to be larger: brush pen producers that reported themselves to be growth-oriented at baseline (about 40% of the sample).[2] In this subsample we find significant and large gains in all key measures listed above. For example, we estimate revenue gains of 43 log points. Thus, the referrals substantially improved the performance of both suppliers and growth-oriented clients, suggesting that eliminating firm-to-firm partnering frictions can generate large gains.

A possible concern with these results, suggested by the network-level crowding out result, is that the difference between treated and untreated firms may be confounded by business stealing. But we show that exposure to business stealing—measured with the share of prior partners receiving the treatment—does not reduce firm outcomes and does not change the treatment effect. Thus, although business stealing affects the network structure, it does not seem to affect firm performance, perhaps because firms find replacement partners in their prior network. A second concern is that we selected the subsample of growth-oriented brush pen producers after the experiment, raising questions about external validity. But when we use firms' less noisy five-point-scale evaluation of their revenue or profit growth, as well as in most results below involving intermediate outcomes, we find significant impacts in the full sample of clients. Thus, it appears that we are simply underpowered in the client sample with traditional performance measures.

A key question is why the referrals generated these large gains in firm performance. We explore this question by looking at intermediate outcomes, and find evidence on two mechanisms. The first concerns product quality and variety. Among suppliers, the treatment increased product quality (as measured by industry experts). Among clients, the treatment increased the likelihood of having a second product and the share of revenue coming from a second product. Since second products in this industry are generally of higher quality and higher price, suppliers and clients appear to have made complementary improvements. Suppliers seem to have improved quality to provide suitable inputs for clients' expansion into a higher-quality second product. These results suggest that improvements in firm-to-firm access can ameliorate the failures of industrial upgrading

[2] We remove make-up pen producers (20% of the sample) because they use a different composition of input materials, suggesting that referrals may have had a smaller effect on them. Within brush pen producers we remove firms that do not report themselves growth oriented because our survey suggests these firms are capacity constrained.

(Verhoogen 2023) and support the importance of a quality complementarity in production networks as a potential driver of the development process (Demir, Fieler, Xu and Yang 2024).

The second mechanism concerns firm-to-firm search. We show that the treatment increased both supplier and client firms' beliefs about the benefit of partners, time spent searching for partners, and number of non-referred partners. These results are consistent with our earlier finding that firms underestimated their satisfaction from the referrals and provide direct evidence that firms under-searched because they undervalued new partners. Undervaluation is a new mechanism for both search and matching frictions in firm-to-firm access, which suggests that credible information about partner quality should be a part of effective policy interventions. These results also suggest that the large impacts of the treatment on firm performance may have been driven not only by the specific referrals we made, but by changing the beliefs of firms.

We turn to estimate the returns from firm-to-firm access. We estimate that the annual profit gains to suppliers were 8 times, and to growth-oriented clients were 17 times the cost of the subsidy. Firms receiving the information referrals could have earned these returns but chose not to, providing further evidence that the friction was not cost based. We then turn to estimate the social return to our intervention, which requires estimating both the producer surplus and the consumer surplus. For the producer surplus we would need to adjust the estimated profit gains with business stealing, but exposure regressions show no business stealing effects on profit in either the supplier-to-client market (as mentioned above) or in the client-to-consumer market. To estimate the consumer surplus, we combine a CES demand model with our treatment effect estimates (Cai and Szeidl 2024). We estimate the annual gain, relative to the cost of collecting the data and making the referrals, to be 10.1 for the producer surplus and 3.4 for the consumer surplus. The implied social return is 1,350% per year, highlighting the importance of improving firm-to-firm access for development.

In Section 4, we report on a small-scale follow-up referral intervention in which, motivated by the results on matching frictions, we explored a new unsubsidized approach to create new links. We prepared a basic marketing offer, including a free sample, on behalf of the supplier, and took it to the client. The marketing offer was about 30% as effective as the subsidy in resolving the matching friction, but came at 0.5% of the cost. Thus, the design of matching programs could further increase the returns from firm-to-firm access.

Our paper builds on a growing literature in development economics studying the impact of market access, reviewed in Verhoogen (2023) and JPAL (2024). Some of this work studies the impact of transportation or communication infrastructure on reducing frictions in firm-to-firm search and improving business performance (Jensen and Miller 2018, Bernard et al. 2019). Other work studies firms' access to consumers or traders in agriculture (Jensen 2007, Bergquist, McIntosh and Startz 2024), firms' access to peer information (Cai and Szeidl 2018, Asiedu, Lambon-Quayefio, Truffa and Wong 2023), firms' selling ability to large buyers (Hjort, de Rochambeau, Iyer and Ao 2024), and market access through the internet (Demir, Javorcik and Panigrahi 2023, Hjort and Tian 2024).[3] A related line of work studies firms' market access in international trade, including the effects of access to foreign buyers (Verhoogen 2008, Atkin et al. 2017a, Alfaro-Ureña, Manelici and Vasquez 2022, Goldberg and Reed 2023), access to foreign suppliers (Amiti and Konings 2007, Halpern, Koren and Szeidl 2015), and air or face-to-face connections (Campante and Yanagizawa-Drott 2017, Startz 2024). Our contributions to these literatures are to study a new intervention directly targeted at making links between spatially close firms; to explore new outcomes related to the network, firm upgrading, and welfare; and to document a belief-based partnering friction.

We also build on research studying firms' non-adoption of profitable practices (Bloom, Eifert, Mahajan, McKenzie and Roberts 2013, Atkin, Chaudhry, Chaudry, Khandelwal and Verhoogen 2017b, Verhoogen 2023). The adoption friction we identify, firms' undervaluation of potential partners, parallels workers' undervaluation of outside options in labor search (Jäger, Roth, Roussille and Schoefer 2024) and consumers' undervaluation of quality in the context of reputation building (Bai 2024). Our contribution is to show the importance of this friction for firm-to-firm access.

Finally, we build on the macroeconomics literature studying production networks, including how the network allocation shapes performance (Oberfield 2018, Eaton, Kortum and Kramarz 2022); the welfare impacts of policies and shocks, such as supplier churn, in networked economies (Liu 2019, Baqaee, Burstein, Duprez and Farhi 2023); and the role of relationship capability in explaining firm performance (Bernard, Dhyne, Magerman, Manova and Moxnes 2022). Our contribution is to

[3] Related work studies the effects of transportation infrastructure on economic activity, focusing on the effects of reducing trade costs (Faber 2014, Donaldson and Hornbeck 2016, Donaldson 2018, Hornbeck and Rotemberg 2024).

evaluate and quantify the welfare impacts of a new intervention creating firm-to-firm links.

1 Context, Data, Design

1.1 Context

Our study area is in a city located in southeastern China, which has a population of approximately 6 million. The city is a major economic hub with a GDP of around RMB 732 billion (USD 104 billion) in 2023. The city contains a county renowned for its production of the Chinese brush pen, an important product in Chinese culture (Chiang 1974, Clunas 1997).[4] Production of brush pens in the county began around 1600 years ago, and earned the county the title "Hometown of China's Writing Brush." In 2021, the county's brush pen was officially recognized as part of China's national intangible cultural heritage.[5] The county hosts a brush trading market, recognized as a central hub for all brush pen products in China, which opens nine times a month and draws about 50,000 traders from all over China. The location dedicated to the production of brush pens consists of 2 main urban areas and 8 rural areas, encompassing 72 streets and natural villages.[6]

The product. The writing brush consists of two main components: the brush head (the hairy part) and the handle. The brush head is generally made of animal hairs or nylon, while the handle is generally made of bamboo or wood. There is much quality differentiation across products, which mainly comes from the brush head. Quality partly depends on the type of hair used, with goat hair and weasel hair being the highest quality, followed by mixed hair which consists of a combination of goat and weasel hair, bristle, horse hair, and nylon. Quality also depends on how well the brush head is made, which can be measured by four standardized criteria that—as local experts explained to us—combine into two main dimensions of the brush head: craftsmanship and durability.[7] The

[4] In China, cities are larger administrative units than counties and generally contain several counties.

[5] See `https://www.ihchina.cn/project.html` for the announcement (retrieved October 2024). Demand for the brush pen is sizable, especially since China's Ministry of Education has repeatedly called for teaching calligraphy in primary and secondary schools (Yuhan 2023). The buyers and consumers of writing brushes include calligraphy lovers, artists, students, educational institutions offering calligraphy and painting courses, tourists purchasing souvenirs, and the high-end gift market since brush pens are often gifts at significant events.

[6] Streets and natural villages are administrative units. Streets are sub-jurisdictions of urban communities, natural villages are sub-jurisdictions of rural communities.

[7] The "four virtues" of a writing brush are that the tip should be sharp (Jian) for precise lines and detailed strokes;

former can be evaluated just by looking at the brush head, while the latter can only be evaluated by writing with the brush pen (see Appendix C for details and pictures).

Supply chain. The supply chain of the writing brush is organized into three layers.

1. Raw materials: firms supplying nylon and animal hairs for the brush head, and bamboo and wood for the handle.

2. **Intermediate inputs:** firms producing the brush heads, firms producing the handles, and processing firms which conduct production but do not own their inputs.

3. **Final goods:** firms purchasing intermediate inputs and services, assembling the final products and selling them to consumers.

Our main focus in this paper will be layers 2 and 3, which contain most of the firms. We will refer to the firms in these two layers as suppliers and clients, respectively. The firms in the three layers are connected by supply chains. Brush head producers purchase nylon and animal hairs while handle producers purchase bamboo and wood from raw material suppliers. Final goods producers purchase brush heads and handles from intermediate input suppliers and production services from processing firms. Many firms engage in multiple activities, for example, producing both the brush head and the final good, but it is possible to classify firms into one of the three layers based on their main activity. The industry features some degree of spatial specialization, e.g., some villages specialize in producing handles, others in producing high-quality brush heads.

In Figure 1 we provide more detail about the characteristics of supplier and client firms. We distinguish between business type and product type. Supplier firms, as noted, have three main business types: brush head producers, handle producers, and processing firms. Among brush head producers, we define the firm's product type by the raw material of its main product: goat hair, weasel hair, or mixed hair. Client firms have two business types: brush pen producers (80%) and make-up pen producers (20%). Among brush pen producers we again define product type by the raw material of the main product (goat, weasel, or mixed hair). Finally, make-up pen producers

the hairs should be even (Qi) for consistent and smooth writing; the brush head should be round (Yuan) to ensure smooth and fluid movement; and the brush should be resilient (Jian) with good elasticity and strength, to quickly return to its original shape after use. These quality components are specified in the Chinese National Standard GB/T 34854-2017: Chinese Traditional Stationery - Writing Brush (SAMR 2017).

manufacture make-up and painting pens, products related to but distinct from the brush pen. These firms generally use mixed hair and pay less attention to quality.

In our location, the production of the brush head is generally done by hand, while the production of the handle involves some use of machines. The industry largely operates under a household workshop model, with each household independently seeking its own market (see Appendix C for details and pictures). This decentralized production provides flexibility, enabling quick adjustments to meet client needs. However, a potential cost is that frictions may prevent firms from finding the best partners, limiting growth.

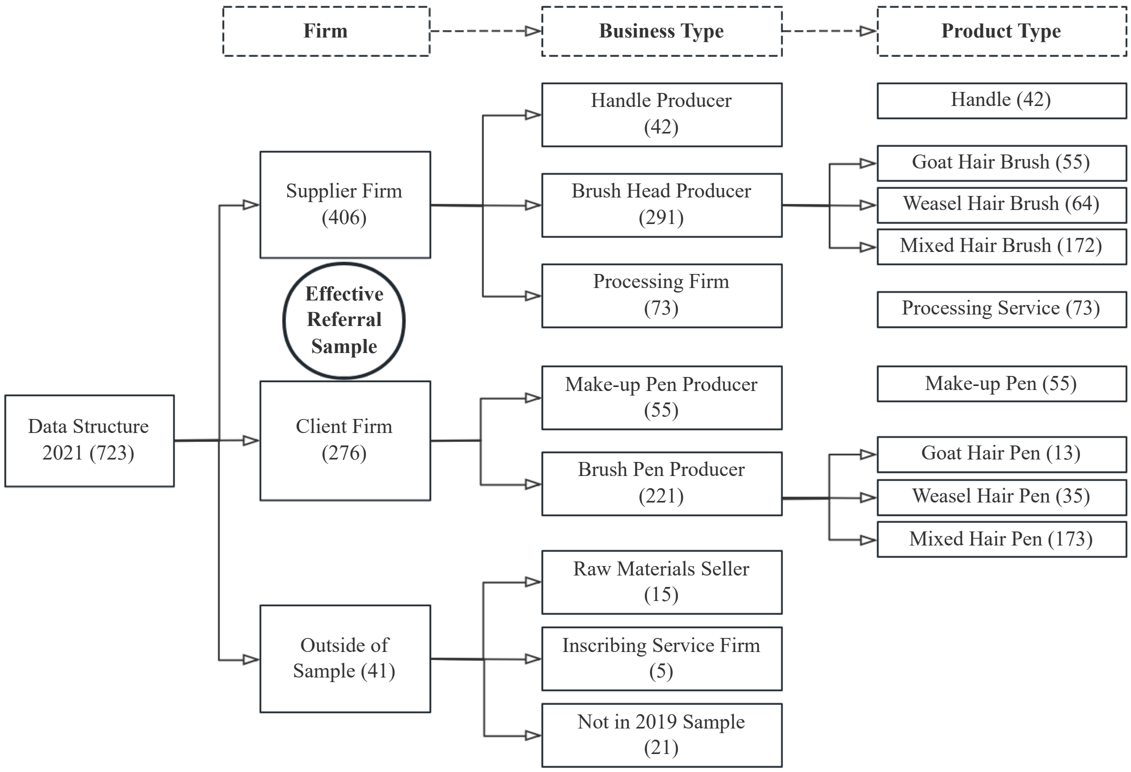
1.2 Data

We started our research activities with the industry in 2018 summer. We started by creating a firm census. We did this taking advantage of two datasets we acquired from the government: (i) a list of registered brush pen producers in each area, which mainly contained the larger firms in the industry; (ii) administrative population census data. To find the smaller firms, we asked the heads of the 72 administrative units in our setting (natural villages and streets) to identify in the population census corresponding to their unit firms active in the brush pen industry. We validated both sources of data by identifying respected elders in each of the 72 administrative units and asking them to verify our list corresponding to their unit. The end result of this process was a list of firms in the industry, including business type, address, owner name and phone number. In our 2018 baseline survey we found 805 of the firms from this list. This is our firm census, and while it is probably not comprehensive, we believe it contains the vast majority of local firms in the industry.

Partly for the current project, and partly for a different project related to e-commerce, we conducted the following five main surveys.

1. Baseline 1: 2018 summer and 2019 spring
2. Baseline 2: 2019 summer
3. Baseline 3 and referral intervention: 2021 summer
4. Follow up 1: 2022 summer
5. Follow up 2: 2023 summer

Figure 1: Structure of data



We also conducted a short phone survey in 2024. We were able to survey a large share of the firms in our census in each survey wave, nearly 90%. Figure 1 presents the data structure in our 2021 baseline, which is the effective baseline for the analyses in this paper. We surveyed 723 firms in total, from which we selected our main intervention sample of 406 suppliers and 276 clients.[8]

In each wave we conducted a firm survey and a network survey. In the firm surveys we collected data on the following main variable types. (1) Firm performance, including sales, profit, employment, and cost. (2) Products. The firm's main products (up to three), including product definition, price, and sales share; and measures of new product introduction. (3) Supply chain. The number of suppliers and clients, the firm's satisfaction with and trust in suppliers and clients, and the firm's valuation of and search for new suppliers and clients. (4) Business practices, includ-

[8] The remaining 41 firms were either raw material producers (15), firms providing inscribing services, a different type of intermediate input (5), or supplier and client firms that were not included in the design because we lacked the 2019 data for them which was necessary to conduct the referrals.

ing time allocation to different tasks such as quality control; simple management practices; and borrowing. (5) Managerial characteristics, including demographics, personal initiative, and trust in other businesses. We note that not all variables were included in all survey waves.

We complemented the firm surveys with quality measured by independent experts. Since quality is largely determined by the brush head, we purchased one item of the main product from most brush head and brush pen producers (and a few other firms) and asked a group of local experts to evaluate their quality. Each good was evaluated by two or three experts. All of the experts we used were national award-winning master producers. The experts grouped items by the type of the raw material of the brush head (goat, weasel, or mixed hair) and within each group gave scores along two dimensions: craftsmanship which can be evaluated by observing the brush pen and durability which can be evaluated by writing with the brush pen.

We conducted the first network survey, which accompanied the 2018 summer firm survey, in 2019 spring. The delay was because in 2018 summer we were occupied by the census and the design of the first firm survey. In later waves we conducted the firm and the network survey simultaneously. Conducting a network survey was initially challenging because firms found it tedious to give detailed information about all of their partners. We therefore created lists of the potential partners of firms based on the baseline firm survey, and asked firms to first identify partners from that list. We created separate lists for supplier firms and for client firms. After firms identified all partners they could find in our lists, we asked them for additional main partners. In subsequent surveys we asked firms about all of their past partners, about our referrals (after the intervention), and asked them to list any additional partners as well. We collected data on the volume and number of transactions and the firm's satisfaction with each partner.

1.3 Design

In the summer of 2021 we conducted an intervention in which we made referrals between supplier firms and client firms. All referrals were constructed based on the set of suppliers and clients in our 2019 sample.[9] We introduced two types of variations in the referrals:

[9] We could not use the 2021 survey yet because the intervention was conducted immediately after the 2021 survey, before the data was cleaned.

1. Unscreened versus screened. These differed in terms of data use: we constructed screened referrals using both the firm and network data, while unscreened referrals using only the firm data. We expected this variation to be informative about the data requirements for scaling referrals.

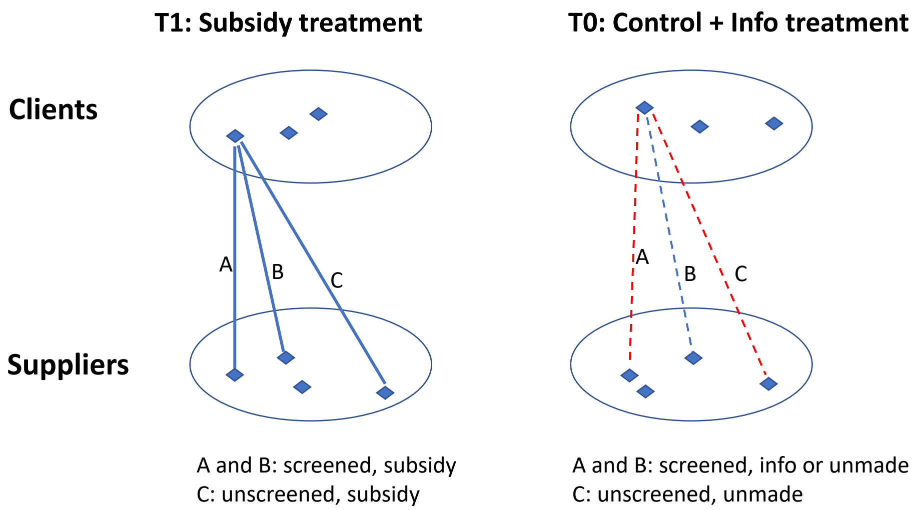
2. Information versus subsidy. For information referrals we only provided information about the partner, while for subsidized referrals we also provided a subsidy for a first transaction. We expected this variation to be informative about matching frictions.

We now turn to explain the construction and implementation of the referrals. We focus here on the main ideas, and include additional details in Appendix D.

Screened and unscreened referrals. The idea of screened referrals was that a supplier-client pair may be a good match if the supplier has one or more close competitors selling to the client, or the client has one or more competitors buying from the supplier. This idea leverages the network data based on the intuition that the existing partnerships of close competitors reflect information about good matches. To it, we first created a measure of close competitors, both for suppliers and clients, based on similarity in product and price. Then, for each supplier and client, we identified the set of potential partners which were not yet partners but were either close competitors of an existing partner or existing partners of a close competitor. We ranked these potential partners by the number of linkages: for example, a supplier selling to more close competitors of the client was judged to be a better potential partner. Finally, we created the referrals using an algorithm that ensured that all firms got some referrals and no firms got too many referrals. This was possible because we could reformulate the problem as one of finding a minimum-cost flow in a weighted network, and then could apply a standard algorithm.

The idea of unscreened referrals was that a supplier-client pair may be a good match if they produce goods which are based on the same type of hair (when applicable). That is, for each client we randomly chose a supplier which was either a handle producer, a processing firm, or a brush head producer using the same type of animal hair (e.g., a goat-hair brush head producer to a goat-hair brush pen producer). For make-up pen producers, since they generally produce form a mix of materials, we did not place any restriction on the referred brush head producer.

Figure 2: Structure of randomization



Information versus subsidy referrals. This variation concerns how we made the referral. In information referrals, we told the two parties that the researchers and the local government are conducting a research study, and we that think that the referred firm would be a good potential business partner. In the subsidy referrals, we also offered a subsidy for the first transaction, which covered 50% of the transaction value up to a cap of 1,500 RMB per transaction, valid for two months. In both types of referrals, we gave coupons to both firms which included the contact details of the referred partner. In the subsidized referrals only the client firm could ask for the 50% subsidy, and to claim it they were required to submit: (1) a video of the face-to-face transaction, (2) both coupons signed by the supplier and the client, (3) an invoice documenting the transaction, and (4) an itemized list of all goods purchased.

Structure of treatments. Figure 2 illustrates the allocation of referrals across firms. First we randomized all suppliers, and all clients, into two approximately equal-sized groups each, T1 and T0. Then we constructed a set of candidate referrals between the T1 suppliers and T1 clients, and another set of candidate referrals between T0 suppliers and T0 clients. As will be clear below, we can think about T1 as treated firms and T0 as untreated firms. The absence of cross-group referrals will allow us to make firm-level comparisons.

For each client firm we constructed two screened referrals, which are labeled by A and B in the figure, and one unscreened referral, labeled by C in the figure. To increase comparability between the screened and unscreened referrals, we ensured that the supplier in the unscreened referral C had the same business type (brush head, handle or processing) as that in the screened referral A. As noted above, we constructed the A and B referrals using an algorithm that ensured that no supplier gets too many links and all suppliers get some links. In practice, all suppliers got at least one screened referral and no supplier got more than four screened referrals.

We then made the referrals. We made all the T1-to-T1 candidate referrals, and all of these were made as subsidized referrals. Among the T0-to-T0 candidate referrals, we made a random half of the B links, and all of these were made as information referrals. The remaining T0-to-T0 referrals, including the remaining B referrals and all A and C referrals, were not made. The reason we made the information referrals in T0—what we intended to be the untreated group—was statistical power: based on a pilot we expected the information treatment to have no effect on subsequent transactions. This was subsequently confirmed in the data. As a result, we can think of T0 as a counterfactual for T1, and we will sometimes refer to firms in T1 as treated and firms in T0 as untreated. In summary, we have four link-level treatment arms, screened subsidy, unscreened subsidy, screened information, and control; and (effectively) two firm-level treatment arms, treated and untreated.

Randomization and implementation. Although the treatment took place in 2021, we constructed the referrals using the 2019 data because the 2021 survey data was not yet ready. In the 2019 data we classified firms based on their main product into business type categories and selected the firms that were either suppliers (brush head producers, handle producers, processing firms) or clients (brush pen producers and make-up firms). We then randomized these firms into T1 and T0, stratifying by business type and baseline sales. Specifically, we divided client firms into brush pen producers and make-up pen producers; and supplier firms into brush head producers and other input suppliers (handle producers and processing firms). Then within each of these groups, we divided firms into ten percentiles based on their 2019 sales. This resulted in 40 strata. In each strata we randomized half of the firms to T1.

We made the referrals in July 2021, around the same time as the 2021 survey. We made the referral to and shared the coupons with each firm only after the 2021 survey for that firm was completed. During the implementation of the survey and the referrals two issues emerged. (i) Some firms went out of business between 2019 and 2021. (ii) Some firms changed their main product and as a result switched roles, from supplier to client or vice versa. To address these issues, we constructed some new referrals to replace the candidate partners lost in change (i) and to create adequate referrals for the firms affected in change (ii). Our final sample consisted of 406 suppliers and 276 clients. The data structure is summarized in Figure 1. We provide more details about the construction and implementation of the referrals in Appendix D.[10]

1.4 Summary statistics and balance

Table 1 presents summary statistics in the 2021 baseline survey about both suppliers and clients. Treatment refers to T1. Columns 1-3 report summary statistics for suppliers. Column 1 shows the mean value for untreated suppliers, column 2 for treated suppliers, and column 3 the difference. Columns 4-6 report summary statistics analogously for clients. Standard errors are in parenthesis.

Panel A focuses on firm characteristics. On average, both suppliers and clients have been in operation for over 20 years. Supplier firms have about 2-3 employees, while client firms have about 6 employees. These values include both formal and informal (e.g., family) employment. Supplier firms' average revenue is about RMB 150,000 (USD 23,000)[11] and their average profit is about RMB 70,000 (USD 11,000) so that profits account for nearly half of revenue. This high share likely reflects that some of the profit is compensation to the owner and their family. Client firms are larger in terms of financial performance: their revenue is about RMB 850,000 (USD 132,000) and their profit is about RMB 370,000 (USD 57,000), so that profits account for over 40% of revenue. The large standard errors indicate that the mean values mask much heterogeneity across the firms in our sample. About 70% of suppliers, and about 46% of clients are growth-oriented, as measured based

[10] In 2019 we introduced another intervention in the same population of firms, in which we encouraged some firms to join a new e-commerce platform designed for this industry. As part of that intervention, we provided firms treated in that intervention both smart phones and training on how to use the platform. The referral treatments are balanced with respect to the e-commerce intervention.

[11] We convert all baseline RMB values to USD using the 2021 average rate of 0.155 USD.

Table 1: Summary Statistics

	Suppliers			Clients		
	Untreated	Treated	Difference	Untreated	Treated	Difference
Panel A: Firm Characteristics						
Firm Age	26.483	26.567	0.084	22.212	20.468	-1.744
	(13.947)	(12.697)	(1.324)	(11.907)	(11.799)	(1.427)
Number of Employees	2.371	2.667	0.296	5.635	5.518	-0.117
	(1.627)	(2.658)	(0.218)	(5.662)	(5.499)	(0.672)
Profit (10,000 RMB)	6.804	8.702	1.898	37.380	37.244	-0.136
	(10.341)	(24.543)	(1.863)	(66.989)	(62.405)	(7.792)
Sales (10,000 RMB)	14.833	16.799	1.966	85.007	86.003	0.996
	(27.422)	(38.271)	(3.299)	(145.306)	(136.645)	(16.976)
Growth Oriented	0.693	0.726	0.034	0.460	0.460	0.001
	(0.463)	(0.447)	(0.045)	(0.500)	(0.500)	(0.060)
Panel B: Managerial Characteristics						
Gender (1=Female, 0=Male)	0.307	0.323	0.016	0.117	0.108	-0.009
	(0.463)	(0.469)	(0.046)	(0.322)	(0.311)	(0.038)
Age	53.600	53.542	-0.058	49.409	48.986	-0.423
	(10.369)	(9.876)	(1.005)	(9.581)	(11.295)	(1.262)
Education- Middle School	0.444	0.478	0.034	0.686	0.741	0.055
	(0.498)	(0.501)	(0.050)	(0.466)	(0.440)	(0.055)
Panel C: Number of Partners (buyers for supplier, sellers for client)						
In Firm Data	5.595	6.647	1.052	6.102	5.619	-0.483
	(9.706)	(13.583)	(1.170)	(7.347)	(6.208)	(0.818)
In Firm Data, Winsorized at 6	3.229	3.294	0.064	3.489	3.540	0.051
	(2.350)	(2.310)	(0.231)	(2.304)	(2.307)	(0.278)
In Network Data, All Partners	2.178	2.439	0.261	3.593	3.587	-0.006
	(2.687)	(3.319)	(0.299)	(3.849)	(3.752)	(0.458)
In Network Data, Supplier-client Links	1.444	1.607	0.163	2.292	2.194	-0.098
	(2.377)	(2.914)	(0.264)	(3.352)	(3.279)	(0.399)
Panel D: Attrition and Shutdown						
Attrition (2021 to 2022)	0.044	0.035	-0.009	0.036	0.029	-0.008
	(0.205)	(0.184)	(0.019)	(0.188)	(0.168)	(0.021)
Attrition (2021 to 2023)	0.063	0.025	-0.039*	0.058	0.086	0.028
	(0.244)	(0.156)	(0.020)	(0.235)	(0.282)	(0.031)
Shutdown (2021 to 2023)	0.029	0.015	-0.014	0.007	0.014	0.007
	(0.169)	(0.122)	(0.015)	(0.085)	(0.120)	(0.013)
P-val of Joint Significance of Vars in Panels A-C (2021 sample)			0.938			0.983
P-val of Joint Significance of Vars in Panels A-C (2023 sample)			0.990			0.986
Observations	205	201	406	137	139	276

Notes: *** p<0.01, ** p<0.05, * p<0.1.

on their response in the 2018 baseline concerning their willingness to expand their business. The vast majority of firms who said no to this question gave the reason that they did not have enough capacity, including management capacity, to expand.[12]Panel B reports managerial characteristics. Essentially all firms are family firms managed by their owner. 69% of suppliers and 89% of clients are managed by men, and the average age of managers is about 53 and 49, respectively.

Panel C provides summary statistics on partnerships. The rows report the number of partners measured in different ways, where partner is defined as buyer for supplier firms and seller for client firms. The first row shows the total number of partners (defined in this way) reported in the firm survey. Suppliers on average sell to about 6 buyers, and clients on average buy from about 6 sellers. As suggested by the large standard errors, these means are partly driven by a few firms with a large number of partners. The second row reports the same measure winsorized at 6 partners. We winsorized to increase comparability with the network data, in which, given the way we collected that data, firms rarely name more than 6 partners.[13] The third row reports the total number of partners in the network data. For clients, this value is almost exactly the same as in the previous row, suggesting that for them our network data is fairly complete for the first 6 sellers—probably the most important sellers—but less complete for additional sellers. For suppliers, the number in the network data is smaller (about 2.2 versus about 3.2), a gap that may reflect the other side of the links that we missed in the client data. The last row table reports on links that are confirmed to be from a supplier firm to a client firm. Suppliers sell to about 1.5 firms in the client sample, and clients buy from about 2.2 firms in the supplier sample. The difference between this row and the previous reflects that for some links we were not able to determine the identity of the partner, and that other links capture a non-supplier-to-client transaction, such as a supplier selling to another supplier. We conclude that our network-level data is close to comprehensive for the most important 5 or 6 links of client firms, which are probably the most important links in the network.

Consistent with the randomization, there is no significant difference between the treatment arms

[12] Growth-oriented firms are significantly smaller than non-growth-oriented firms, suggesting that when the firm reaches a certain scale it faces constraints to further growth, perhaps because of the difficulty of hiring or managing non-family workers.

[13] We collected the network data by first asking firms to name up to five partners from the list of potential partners we showed them, and then asking them to name up to 5 non-listed partners. Among firms that named a non-listed partner, they named on average about one such partner.

in any of the variables in Panels A-C. Moreover, as the p-values in the bottom show, regressing the treatment indicator on all the variables in Panels A-C yields no evidence of joint significance.

Panel D reports attrition and shutdown. Attrition is defined as one in a survey wave if we do not have information about the firm in that wave and do not know whether the firm has shut down. This is typically due to the manager of the firm not being available at the time of our visit. Shutdown is defined as one in a survey wave if we have information that the firm was not in business at the time the survey was conducted. With these definitions, attrition and shutdown are mutually exclusive. Shutdown is about 2 percent for suppliers and 1 percent for clients and balanced across the treatment arms. Attrition is always below 10 percent, is balanced in 2022 for both suppliers and clients, and is balanced in 2023 for clients. However, attrition shows a significant imbalance of 4 percentage points in 2023 for suppliers.[14] This imbalance raises the potential threat of selective attrition. To address it, we have conducted balance tests in the subsample of firms that remain in the data. Regressing the treatment on the baseline value of all variables in the table in this subsample shows the joint insignificance of these variables. And reproducing the entire balance table for this subsample in the Appendix Table A1 shows essentially identical results as the table shown here. We conclude that selective attrition is unlikely to bias our results.

1.5 Take-up

Before analyzing the impact of the referrals, we look at take-up. We have a well-defined measure of take-up for the subsidy treatment, because we know whether the referred firms received the subsidy for an initial transaction. We begin with regressions of the form

$$Takeup_i = \mu \cdot \mathit{Treatment}_i + Controls + \nu_i. \tag{1}$$

Here each observation is a firm i, the outcome variable is an indicator for whether the firm used the subsidy for any of its referred links, and the key independent variable is whether the firm is in the treatment group (T1). Recall that all firms in the treatment group received subsidized referrals. The controls include strata fixed effects and we cluster standard errors by firm.

[14] Attrition is lower in 2023 than in 2022 for treated suppliers because we were able to survey some firms in 2023 that we could not survey in 2022.

Table 2: Take-up of subsidy

Dep. var.: subsidy used	Clients (1)	Suppliers (2)	Links (3)	Links (4)
Treatment	0.609***	0.631***	0.484***	
	(0.041)	(0.034)	(0.039)	
Screened				0.474***
				(0.039)
Unscreened				0.504***
				(0.047)
Information				
Strata FE	Yes	Yes		
Business type FE			Yes	Yes
Observations	276	406	856	856

Notes: In columns 1 sample is client firms, in column 2 supplier firms, in columns 3-4 all referrals, actual and hypothetical. In columns 3-4 firm business type effects are included for both supplier and client. In columns 1-2 standard errors clustered by firm, in 3-4 by supplier and client. *** p<0.01, ** p<0.05, * p<0.1.

Table 2 reports the results. Column 1 shows that in the subsample of client firms, about 61 percent of treated firms used the subsidy on at least one of their referred links. Column 2 shows that in the subsample of supplier firms, about 63 percent of treated firms used the subsidy on at least on of their referred links. The coefficients are highly significant. These results indicate that firms valued the subsidized referrals.

We are also able to look at take-up at the link level, which allows us to separately measure the take-up of screened and unscreened referrals. To do this, we estimate regressions similar to (1) but in the sample of all *candidate referral links*, including the T1-to-T1 and the T0-to-T0 referrals. Treatment refers to the subsidy treatment, i.e., the T0-to-T0 referrals are the control group. In this regression we control for the business type of both the supplier and the client and cluster standard errors by supplier and by client. Column 3 shows that firms used the subsidy on about 48 percent of treated links. In column 4 we measure take-up separately for screened and unscreened referrals, and find that there are essentially the same, about 48 and 50 percent respectively. Thus, firms valued subsidized referrals irrespective of whether they were screened.

2 Effects on the network

2.1 Link creation

We now turn to measure the impact of referrals on the firm-to-firm network. We start by looking at link creation, measured with subsequent transactions on treated links after the end of the subsidy period. Our empirical specification is

$$\begin{aligned} y_{ijt} = \beta_S \cdot \textit{Screened subs}_{ij} + \beta_U \cdot \textit{Unscreened subs}_{ij} + \beta_I \textit{Info}_{ij} \\ + \textit{Referral type f.e.} + \textit{Business type f.e.} + f_t + \varepsilon_{ijt}. \quad (2) \end{aligned}$$

Here each observation is a link ij in a follow-up survey wave t of 2002 or 2023. The sample is all candidate referrals we constructed, both made and not made, that is, the subsidized referrals (T1-to-T1), the information referrals (a quarter of the T0-to-T0), and the referrals we constructed but did not make (the rest of the T0-to-T0). The outcome variables measure subsequent transactions. The key right-hand-side variables are indicators for making the screened subsidy referral, the unscreened subsidy referral, and information referral (all information referrals were screened). The controls include indicators for the type of the candidate referral (A, B, or C as defined in Section 1.3, which span whether the candidate referral was screened or unscreened), indicators for the firm's business type (as defined in Figure 1) and year effects. We cluster standard errors by supplier and by client. Because the treatments are randomized, the key coefficients should measure the causal effect of making the different types of referrals.

Table 3 reports the results. In column 1, the outcome is an indicator for a transaction over link ij in year t. A subsidized screened referral increases the probability of a subsequent transaction by 45 percentage points, while a subsidized unscreened referral increases that probability by 29 percentage points. Both coefficients are highly significant. In contrast, a screened information

Table 3: Link creation

Dep. Var.:	Link	Num Transactions	Value (RMB)
	(1)	(2)	(3)
Screened Subsidy	0.455***	2.714***	7,863.811***
	(0.041)	(0.329)	(1,166.094)
Unscreened Subsidy	0.288***	1.259***	3,362.326***
	(0.033)	(0.191)	(651.598)
Information	-0.029	0.179	1,365.964
	(0.046)	(0.361)	(1,196.802)
Referral type, business type, year FE	Yes	Yes	Yes
Observations	1,707	1,707	1,707

Notes: Sample is all referrals, actual and hypothetical. Referral type fixed effects mean referral type A, B or C. Business type effects capture main business activity (e.g., brush head producer). Standard errors clustered by supplier and client. *** p<0.01, ** p<0.05, * p<0.1.

referral has a small and insignificant effect on subsequent transactions. Columns 2 and 3 report impacts on the number and total value of transactions. The results are analogous.

These findings have several implications. First, the large impacts imply that partnering frictions are potentially important. Even though the firms have been active in the industry for over 20 years, are in the same county, and even have access to a centralized marketplace, our referral intervention managed to create many new partnerships. Second, the higher impact of screened than unscreened referrals suggest that there is value to using richer data for screening. Third, the null effect of information referrals implies that even conditional on finding a potential partner, firms have difficulty initiating a relationship, indicating a matching friction.[15]

We turn to explore whether firms are satisfied with the referrals. In the follow-up surveys, for each candidate referral—both made and unmade—we asked both firms to rate on a 10-point scale how satisfied they are, or think they would be, with the referred partner.[16] We standardized

[15] We note that the vast majority of firms did not know the referred partners, so the reason for the failure of the information treatment is not that firms already had the contact information of the referrals.

[16] For firms that were unable to answer the question, we asked how satisfied they expected they would be with

Table 4: Satisfaction with new referrals

Dep. Var.:	Client satisfaction			Supplier satisfaction		
	Price	Product	Overall	Price	Demand	Overall
	(1)	(2)	(3)	(4)	(5)	(6)
Screened Subsidy	0.350***	0.380***	0.397***	0.629***	0.723***	0.616***
	(0.099)	(0.095)	(0.098)	(0.115)	(0.120)	(0.119)
Unscreened Subsidy	-0.015	0.063	0.016	0.502***	0.489***	0.511***
	(0.090)	(0.089)	(0.092)	(0.113)	(0.123)	(0.123)
Information	-0.010	-0.102	-0.079	-0.040	0.007	-0.102
	(0.068)	(0.063)	(0.063)	(0.139)	(0.142)	(0.137)
Referral type, product type, year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,572	1,572	1,571	1,609	1,609	1,608

Notes: Sample is all referrals, actual and hypothetical. Outcome variable standardized in each column. Referral type fixed effects mean referral type A, B or C. Business type effects capture main business activity (e.g., brush head producer). Standard errors clustered by supplier and client. *** p<0.01, ** p<0.05, * p<0.1.

firms' responses and report the treatment effects on the resulting measures in Table 4. The screened subsidy improved the expected satisfaction of suppliers by a significant 0.6 standard deviations, and that of clients by a significant 0.4 standard deviations. The unscreened subsidy also significantly improved the expected satisfaction of suppliers, but not that of clients. The information referral had no effect, which is unsurprising since it did not generate transactions.

The on-average increases in expected satisfaction are inconsistent with Bayesian updating under a correct prior: if beliefs about the value of partners are correctly calibrated, then the treatment should not change average satisfaction. Thus, the results show that firms on average undervalued the partners we referred to them. This undervaluation is a possible mechanism for the matching friction that made the information treatment ineffective: firms may not have approached the referred partners because they falsely thought them unsatisfactory. This logic suggests that miscalibrated beliefs may be an important barrier to firm-to-firm access, which is not easily overcome by providing information about potential partners.

an unknown partner from the county. We think that this is a good measure of their expected satisfaction from the referral since the reason they were unable to answer is that they had limited information about the referred partner.

To shed further light on the nature of frictions, we surveyed the firms receiving the information treatment and asked them why they did not take that up. The two most salient answers were that (i) firms were not certain the partner would be a good match for them (49% of clients, 33% of suppliers); and (ii) firms did not know how to approach the partner and are afraid of rejection (23% of clients, 46% of suppliers). Answer (i) is consistent with these firms, especially clients, underestimating the value of referrals. Answer (ii) suggests that there may be another friction at play, particularly for suppliers, related to the lack of marketing skills (Hjort et al. 2024).

The null impact on the satisfaction of client firms from unscreened referrals implies that these firms were well-calibrated for a random referral, suggesting that for them much of the gain came from screened referrals. Motivated by this finding, we compare the characteristics of screened and unscreened referrals in Appendix Table A2. We find that in screened referrals suppliers and clients are closer to each other in price, which is a proxy for quality, as well as in space. Thus, screened referrals appear to be a better match in observable dimensions.[17]

The potential importance of match quality leads us to estimate a heterogeneous effect version of our link creation regression (2). Appendix Table A3 reports the results. The referral is more likely to lead to links when the seller or the buyer are larger in terms of revenue, when their price is closer, and when the seller and the buyer are kin. These results provide further evidence for the importance of match quality, and suggest that match quality is partly firm specific, so that bigger partners are better, but partly match specific, so that similar-quality partners are better. We unfortunately lack the power to investigate these issues further.

[17] In screened referrals suppliers and clients differ more from each other in terms of log revenue. This is likely the result of two factors. First, there is a slight negative assortativity between supplier and client revenue in the transaction network, which may be inherited by our network-based screening. Second, the balancing requirement of our matching algorithm may have amplified this: Ensuring that all suppliers get referrals may have led to assigning large clients for small suppliers, making these large clients unavailable for larger suppliers.

Table 5: Link destruction

Dep. Var.:	Link	Num Transactions	Value (RMB)
	(1)	(2)	(3)
Client Treated * Supplier Treated	-0.208***	-1.420	-18,457.623**
	(0.050)	(1.083)	(8,256.183)
Client Untreated * Supplier Treated	-0.181***	0.185	-13,424.635*
	(0.044)	(2.042)	(7,065.487)
Client Treated * Supplier Untreated	-0.198***	-1.966**	-21,845.341***
	(0.053)	(0.931)	(6,922.504)
Business type, year FE	Yes	Yes	Yes
Observations	1,238	1,238	1,238

Notes: Sample is pre-existing links. Business type fixed effects capture main business activity (e.g., brush head producer). Standard errors clustered by supplier and client. *** p<0.01, ** p<0.05, * p<0.1.

2.2 Link destruction

The new partnerships created by our referrals may have crowded out some existing links through a business stealing effect in the firm-to-firm network. We explore this effect by estimating

$$y_{ijt} = \gamma_C \cdot \textit{Supplier untreated}_i \times \textit{Client treated}_j + \gamma_S \cdot \textit{Supplier treated}_i \times \textit{Client untreated}_j$$
$$+ \gamma_{SC} \cdot \textit{Supplier treated}_i \times \textit{Client treated}_j + \textit{Business type f.e.} + f_t + \varepsilon_{ijt}. \quad (3)$$

The sample for this regression is the set of links between suppliers and clients that existed in our 2021 baseline, in the follow-up years 2022 and 2023. The outcomes are measures of transactions between i and j. The key independent variables are indicators for the client only, the supplier only, or both the client and the supplier receiving the treatment (T1). Thus, the coefficients of interest measure whether pre-existing partnerships change differentially when either the supplier, or the client, or both receive the referral treatment. Controls include indicators for business type and year, and we cluster standard errors by supplier and client.

Table 5 reports the results. Column 1 shows that relative to links in which neither firm is treated, treating either firm results in a reduction in the probability of the partnership of about 20 percentage points. The effects are similar irrespective of whether it is the client, the supplier, or both who receive the treatment. The impacts on the number of transactions (column 2) are noisier and less conclusive, but the impacts on total transaction value (column 3) are all negative and significant. Taken together, these results show that—consistent with the logic of business stealing—the referrals not only created new links but also destroyed existing links.

To explore which links are crowded out, in Appendix Table A4 we estimate heterogeneous-effect versions of regression (3) in which we interact an indicator for either firm being treated (labelled exposure) with different firm and link characteristics. To increase precision, we include the inverse hyperbolic sine of the number of transactions and the value of transactions as additional outcomes. Although power is generally weaker than in our main link-level regressions, some patterns emerge. Perhaps most interestingly, the link is more likely survive if at baseline either the supplier expressed higher satisfaction with the client or vice versa. The link is also more likely to survive if the supplier has higher log sales and if the two firms are kin. The heterogeneous effects by satisfaction show that better matches were more likely to survive, again highlighting the importance of match quality, and suggesting that business stealing may have contributed to improving the allocation of links. The heterogeneous effects by kin have two interpretations: they could reflect economic efficiency if kin captures trust, or economic inefficiency if kin captures social obligations. We lack the power to investigate these heterogeneities in more depth.

3 Effects on firms

The results so far show that referrals meaningfully rewired the firm network. These results may be consistent with two views about the impact of firm-to-firm access on industry performance. View 1 says that the changes in the network reflect marginal improvements: firms merely used the referrals to replace some pre-existing partners, but did not expand activities. Under this view, frictions in firm-to-firm access are not a major growth barrier. View 2 says that the new partnerships, by increasing the market size for suppliers and the input base for clients, enabled firms to expand and upgrade production. Under this view, frictions in firm-to-firm access may be an important growth barrier.

To distinguish between these views, we estimate impacts on firm performance using the estimating equation

$$y_{it} = const + \beta_1 \cdot Treated_i + \beta_2 \cdot y_{i0} + Controls + Strata\ f.e. + f_t + \varepsilon_{it}. \tag{4}$$

Each observation is a firm i in a time period t. We estimate this regression in the 2022 and 2023 follow-up data. The outcome variable is a measure of firm behavior or performance, such as log revenue. The key independent variable is an indicator for the firm's treatment status (T1). When available, we include the baseline value of the outcome variable as a control to reduce noise (McKenzie 2012). We always include strata fixed effects and time fixed effects, and depending on the specification we may include other controls as well.

This regression measures the average difference in the performance of treated versus untreated firms following the treatment. In the absence of indirect effects, β identifies the effect of the treatment on business performance. In the presence of indirect effects, particularly business stealing in the supplier-to-client market, β reflects some combination of the direct and the indirect effect. In Section 3.2 below we present evidence that—despite the link-level business stealing documented earlier—there are no business stealing effects on firm performance, supporting the interpretation of β as a treatment effect. We cluster standard errors at the firm level because indirect effects do not appear to be important and the treatment is randomized at the firm level in a non-clustered fashion (Abadie, Athey, Imbens and Wooldridge 2022).

3.1 Main results

Table 6 reports the impacts on main firm performance measures. Panel A focuses on suppliers. Column 1 shows that treated suppliers, relative to untreated ones, experienced a significant increase in revenue of 24 log points. They also experienced a significant increase in profit of 15,000 RMB, about 19 percent of the profit of untreated firms.[18] There is no detectable impact on operating cost, but columns 4 and 5 show significant increases in log employment and the total number of hours worked by all people in the firm. Thus, treated suppliers substantially increased their activity. Turning to impacts on the firm's network, column 6 shows an increase in the number of suppliers,

[18] Because profit can be negative we did not take logs, and to address outliers we winsorized level profit at the 99th percentile. We used the same procedure for the number of suppliers and clients in columns 6 and 7.

Table 6: Firms: main outcomes

Dep. Var.:	Log Sales	Profit (10,000 RMB)	Log Operating Cost	Log Employ-ment	Total Hrs Worked / Day	Num Reg Supplier	Num Reg Client	Satisfaction Clients / Suppliers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Suppliers								
Treatment	0.244***	1.501*	0.051	0.068*	2.693**	0.373*	1.876**	0.219***
	(0.074)	(0.824)	(0.098)	(0.040)	(1.345)	(0.209)	(0.761)	(0.064)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	1.890	6.804	1.296	0.711	18.82	2.571	5.595	5.059
Observations	761	763	652	763	763	763	763	761
Panel B: Clients								
Treatment	0.042	0.152	0.023	0.050	-0.958	1.608**	0.889	0.241***
	(0.113)	(3.916)	(0.123)	(0.067)	(3.861)	(0.672)	(1.835)	(0.071)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	3.340	37.38	2.740	1.349	39.78	6.102	15.74	5.308
Observations	520	520	502	520	520	520	520	496

Notes: Sample in Panel A is suppliers, in Panel B is clients. In columns 2, 6 and 7 outcome is winsorized at the 99th percentile in each sample, in column 8 satisfaction is with clients in Panel A and with suppliers in Panel B, and is standardized. Baseline value of the outcome variable is included when available, not in column 5 because we did not collect that variable at baseline. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

and column 7 an increase in the number of clients, both significant. The latter is not surprising given that our intervention referred clients to these firms, but does indicate that the link-level crowding out documented earlier did not fully undo the effects on link creation. Finally, column 8 reports a positive effect on treated firms' reported overall satisfaction with clients, providing further evidence that the referrals improved suppliers' pool of partners. These results show that the referrals meaningfully improved the performance of suppliers.

Panel B turns to client firms. Here the estimates are generally insignificant. We find no detectable impact on revenue, profit, cost, or employment. However, perhaps unsurprisingly given the nature of our intervention, there is a significant positive effect on the firm's number of suppliers, and overall satisfaction with suppliers, providing evidence that the referrals also improved client firms' pool of partners.

The lack of significant effects for client firms may reflect that these firms did not experience meaningful gains, or that we lack the power to measure these gains, perhaps because they are concentrated in a subset of firms. To explore the second alternative, we have selected a subset of client firms where we expect the intervention to be particularly effective. First, we removed client firms whose main business is to produce make-up pens, about 20 percent of our client sample. Make-up pen producers use a different composition of input materials and value quality less, suggesting that the referrals had a smaller impact on them; and are either much larger or much smaller than brush pen producers, contributing noise to the estimates. Second, we divided the remaining sample of brush pen producers into growth-oriented versus non-growth-oriented based on their response to the corresponding survey question in the 2018 baseline. As we discussed in Section 1.4, non-growth-oriented firms generally lacked the capacity or aspiration to expand in response to new business opportunities. The subsamples of growth-oriented and non-growth-oriented brush pen producers are roughly of equal size.

Table 7 reports the results from estimating our main specification in these two subsamples. Panel A focuses on growth-oriented brush pen producers. The results in this subsample are large and significant. Treated firms experienced a revenue gain of about 43 log points, and a profit gain of about RMB 84,000, which is about 31 percent of the control mean. Their operating cost, number of workers, and total number of hours worked also increased significantly. And they experienced a significant increase in the number of suppliers and satisfaction with their suppliers. In contrast, the results for non-growth-oriented brush pen producers are insignificant for all outcomes except for their satisfaction with suppliers. As noted, the differences in precision across these two subsamples are not driven by differences in sample sizes.

The results for suppliers are consistent with view 2 above that these firms used the referrals not only to replace marginal partners but to expand their business. The results for clients suggest that among these firms there were two distinct business models. Non-growth-oriented firms used the referrals merely to improve the pool of suppliers (view 1), while growth-oriented firms used the referrals to expand their business (view 2). We conclude that improving firm-to-firm access can generate large gains by enabling both suppliers and clients to expand production, and that these

Table 7: Client firms: main outcomes by growth orientation

Dep. Var.:	Log Sales	Profit (10,000 RMB)	Log Operating Cost	Log Employ-ment	Total Hrs Worked / Day	Num Reg Supplier	Num Reg Client	Satisfaction Suppliers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Growth-oriented brush pen producers								
Treatment	0.425**	8.387*	0.505***	0.232**	8.547**	2.641***	2.822	0.241**
	(0.180)	(4.325)	(0.185)	(0.106)	(4.206)	(0.797)	(1.901)	(0.106)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	2.735	22.48	2.075	1.091	28.24	5.020	12.49	4.889
Observations	202	202	191	202	202	202	202	187
Panel B: Not growth-oriented brush pen producers								
Treatment	-0.045	-1.459	-0.146	0.000	1.652	1.482	-0.630	0.204*
	(0.179)	(7.779)	(0.189)	(0.113)	(7.213)	(1.393)	(4.010)	(0.106)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	3.877	50.91	3.282	1.483	49.32	7.754	21.28	5.766
Observations	214	214	211	214	214	214	214	209

Notes: Regressions in subsamples of client firms. Sample in panel A is growth-oriented brush pen producers, in Panel B is non-growth-oriented brush pen producers. In columns 2, 6 and 7 outcome is winsorized at the 99th percentile in each sample, in column 8 satisfaction is with suppliers and is standardized. Baseline value of the outcome variable is included when available, not in column 5 because we did not collect that variable at baseline. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

effects are largest in firms that have free capacity to expand.

3.2 Concerns with measurement, identification and interpretation

We discuss several potential concerns with our main results.

Indirect effects. One key concern is that the treatment induced indirect effects on firm performance, confounding our interpretation of the estimates as the direct effect of referrals. A salient indirect effect is business stealing in the supplier-client market, through the logic that treating a firm's pre-existing partner, via the possible loss of that partner—as documented in Section 2.2—leads to lower performance. But it is unclear whether the loss of the treated partner actually affects firm performance, since firms may be able to use their network of past partners or the centralized market to find replacement partners.

To explore this issue, we introduce a measure of exposure to business stealing. We define this measure as the share of the firm's baseline partners (sellers for a client firm, buyers for a supplier firm) which are treated. To account for the fact that firms typically have more partners than we observe in our network data, the denominator in this measure is the total number of partners reported by the firm.[19] If business stealing effects are important, then an exogenous increase in exposure should negatively predict business performance. Importantly, because the treatment is randomized, exposure does have a random component driven by the experimental variation in the number of partners treated. However, because firms also tend to have partners outside of our experimental sample, exposure also has a non-random component. To isolate the purely random component, motivated by Borusyak and Hull (2023), we compute the expected exposure of each firm, where the expectation is taken over counterfactual realizations of our randomization. We do this by redrawing our treatment assignment 1000 times, computing each firm's exposure in each draw, and taking the average. We then include expected exposure as a control in the regression. The remaining variation in exposure should be purely random, an assumption we confirm with balance tests (not reported).

Appendix Table A5 reports the results from regressing the main outcomes on the treatment and exposure (controlling for expected exposure). The coefficients of the treatment have very similar magnitude and significance to those in Table 6 above. Exposure does not meaningfully predict firm performance for suppliers, and if anything, has a positive effect on profit and employment for clients. Estimating the same regression in the growth-oriented and non-growth-oriented subsamples (Table A6) leads to similar conclusions: the treatment effects are essentially unchanged in magnitude and significance, and exposure effects are if anything, marginally positive for employment in growth-oriented brush pen producers. The positive exposure effects may be due to treated suppliers providing higher value to their pre-existing clients, perhaps because these suppliers upgraded product quality (as we show below). We lack the power to explore this effect more fully, but the key point is that even this potential positive spillover does not affect the coefficient of the treatment.

[19] As Table 1shows, suppliers in the firm data report on average 6 buyers, while in the network data we identify only 3.5 buyers and only 1.5 buyers which are client firms. For clients, the analogous numbers are 6, 4.5, and 2.2.

We conclude that indirect effects in the supplier-client market do not affect the interpretation of the main results in Section 3.1.

A second type of indirect effect may arise because of business stealing in the final goods market. As treated client firms improve performance, they may attract consumers away from competitor client firms (Cai and Szeidl 2024). Since the treatment is randomized, we expect that this type of business stealing would affect treated and untreated firms equally, implying that to a first approximation it should not bias the regression coefficients. But we can also test for it directly, by including in the regression the share of the firm's competitors which are treated. We define the firm's competitors to be other firms who have the same product type for their main product and are in the same location.[20] Balance tests (not reported) confirm that this share is uncorrelated with baseline characteristics. Tables A7 and A8 show that the share of competitors treated has an insignificant effect on firm performance and does not change the magnitude or significance of the treatment effect. We conclude that business stealing in the final goods market does not affect the interpretation of the main results.

Sample selection. A second concern is that we selected the subsample of growth-oriented pen brush producers after the intervention, so that the external validity of these results may be lower. We address this concern in multiple ways. First, we note that we selected the subsample based on the logic that these are the client firms that are most plausibly receptive to the treatment: they produce the main product of the industry and are oriented towards growth. Second, in this subsample we find significant positive impacts on the majority of outcomes, while in the similar-sized non-growth-oriented subsample we find insignificant impacts for essentially all outcomes. Third, in almost all subsequent results on intermediate outcomes we detect significant impacts in the full sample of clients as well, which are meaningfully stronger in the growth-oriented subsample. Fourth, and most important, we directly document gains in headline performance measures in the full sample of clients using data from the 2024 phone survey, in which we asked firms to rate the performance of their business since 2020 on a five-point scale in the domains of product variety,

[20] Location is either an urban area or one of eight rural areas, called administrative villages (not to be confused with natural villages). Further restricting competitors to have a similar product price does not affect the qualitative results. In this analysis we do not need to introduce the Borusyak and Hull (2023) correction because we only consider competitors that are in the sample, as those firms are plausibly the closest competitors.

total quantity sold, average quality, average price, revenue, and profit. Appendix Table A9 shows significant positive effects on all these outcomes in the full sample of clients.[21] These results support the view that the positive effects for growth-oriented brush pen producers are externally valid.

Experimenter demand. A third concern is that treated firms, in exchange for the subsidy, may have over-reported their performance in the surveys. We address this concern using two sets of outcomes plausibly robust to experimenter demand effects. First, in the 2023 endline we collected data on the owner's phone use, including the value of their monthly bill and the number of calls they made. Second, in the same survey, we asked our enumerators—who did not know the treatment status of the firm—to measure the firm's operations during their visit: count the number of visitors in the firm and the number of calls the owner makes, rate how busy the owner is on a five-point scale, count the number of employees visibly present, and assess overall operations on a 5-point scale.[22] Appendix Table A10 shows, among suppliers, a positive and significant effect for five of these seven outcomes. Among clients there is a positive and significant effect for only one, the log phone bill; but Appendix Table A11 shows in the subsample of growth-oriented brush pen producers a positive and significant impact for four of the outcomes. We conclude that experimenter demand is unlikely to drive our results.

Dynamics. Even if the referrals improved business performance, one may be concerned that these improvements may be short-lived: once firms learn about the referrals, they may choose to switch back to their old partners. To explore the persistence of the firm-level impacts, in Appendix Tables A12 and A13 we include the interaction of the treatment and an indicator for 2023, the second follow-up year after the intervention. We find no evidence that the effects are different in 2022 and 2023. A second piece of evidence on persistence comes from our 2024 phone survey, in which we asked firms to report their performance since 2020 on a 5-point scale. As we discussed above, Appendix Table A9 shows significant gains for revenue, profit, and a number of other outcomes. We conclude that the referrals generated persistent improvements in firm performance.

[21] The treatment effect in this comparison may be mildly confounded by the marketing offer intervention, described below, which we introduced among untreated firms in 2024. Since that intervention had positive effects on link creation, if anything it might bias the treatment effect estimate downwards. But since our outcomes are for the entire 2020-24 period, these changes in the last few months should have only minor effects.

[22] In this scale, 1 represents "extremely poor, on the verge of closing down," while 5 represents "highly prosperous, business is thriving."

Table 8: Product upgrading

Dep. Var.:	Quality score main product			Quality	If 2nd	Share 2nd	Avg Log
	Craftsmanship	Durability	Total	check hrs/wk	product	product	Price
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Suppliers							
Treatment	0.264***	0.258***	0.265***	4.329***	0.029	2.889*	0.095
	(0.087)	(0.090)	(0.087)	(0.794)	(0.035)	(1.541)	(0.080)
Baseline Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	-0.198	-0.191	-0.198	1.759	0.449	14.05	0.558
Observations	408	408	408	763	763	763	624
Panel B: Clients							
Treatment	0.217*	-0.023	0.067	2.446**	0.091**	5.777***	0.187*
	(0.121)	(0.132)	(0.124)	(0.959)	(0.036)	(1.586)	(0.113)
Baseline Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	-0.351	-0.382	-0.382	6.033	0.715	19.33	1.388
Observations	292	292	292	520	520	518	496

Notes: Quality score in columns 1-3 is evaluated by experts, residualized by product type and standardized. In column 7 average log price is the average of the log prices of the firm's main products we collect data on, up to three. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

3.3 Intermediate outcomes and mechanisms

How did the referrals enable firms to expand their business? To better understand the underlying mechanisms, we explore impacts on two sets of intermediate outcomes.

Product upgrading. A salient mechanism is product upgrading: for example, improvements in the pool of their clients may have incentivized supplier firms to invest in product quality (Verhoogen 2023). As discussed in Section 1.2, we measured the quality of the firm's main product—if it was a brush head or a brush pen—with the evaluation of independent experts. The experts produced scores for the product's craftsmanship and durability, which we residualized by product type (i.e., hair type) and standardized. The resulting two measures and their sum serve as our main quality outcomes. We also collected information on the firm's (up to) three most important products, including their price and revenue share, and on the amount of time the firm spends doing quality control.

Table 8 reports impacts on these product-related outcomes. Among supplier firms (Panel A) the referrals generated significant improvements in the main product's craftsmanship, durability, as well as overall quality. These improvements were accompanied by an increase in the time spent on quality control. There is also some evidence for an increase in product variety: treated suppliers experienced an increase in the share of their sales of a second product.

Among client firms (Panel B) we find some evidence of an improvement in quality, but the main effects are in product variety. The treatment increased the likelihood that the firm has a second product, and the share of firm revenue coming from the second product. The treatment also increased the average price of the firm's product portfolio. This effect is driven by client firms' second product being on average more expensive: client firms in our industry tend to have a low-price low-quality main product, and a higher-price higher-quality second product. Consistent with client firms expanding their sales of a higher-quality second product, they also spent more time on quality control. As we show in Appendix Table A14, the results for client firms are stronger in the subsample of growth-oriented brush pen producers.

An intuitive narrative that links these findings is that treated clients used the intermediate input coming from their new suppliers to expand the production of their second product; and this second product, being of higher quality, required treated suppliers to improve quality. In this narrative suppliers and clients upgrade in a complementary fashion: suppliers increase product quality because clients expand product variety, and clients expand product variety because suppliers increase product quality. Thus, our findings support the importance of a quality complementarity between suppliers and clients in production networks, which is a potentially key driver of the development process (Kremer 1993, Demir et al. 2024). They also suggest that an important reason for the puzzling lack of industrial upgrading in the development context (Verhoogen 2023) may be frictions in firm-to-firm access.

Search. The second set of outcomes we consider relate to search for partners. Studying search is natural given that in Section 2.1 we found that firms were positively surprised by their referred partners. In the 2023 endline we asked firms their beliefs about the benefit of finding new partners,

Table 9: Search

Dep. Var.:	Perceived profit growth if new client %	Search new clients hrs/month	Perceived profit growth if new supplier %	Search new suppliers hrs/month	Personal initiative	Num non-referred partners
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Suppliers						
Treatment	11.051***	8.645***	0.957	1.038	0.307***	1.362*
	(1.453)	(1.358)	(0.712)	(0.633)	(0.070)	(0.762)
Baseline Control, Year FE						Yes
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	4.99	4.53	1.14	1.24	3.75	5.595
Observations	374	374	374	374	373	763
Panel B: Clients						
Treatment	-0.933	0.732	2.302***	2.713**	0.074	1.159
	(1.346)	(2.030)	(0.799)	(1.365)	(0.083)	(1.416)
Baseline Control, Year FE						Yes
Strata Fe	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	6.74	8.05	2.41	3.09	3.92	6.248
Observations	251	251	251	251	251	520

Notes: Outcomes in columns 1-5 collected in the 2023 survey. Outcome in column 5 is averge response to seven questions on personal initiative. Outcome in column 6 is number of partners (clients in Panel A, suppliers in Panel B) reported in the firm data minus number of referred partners reported in the network data. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

measured as the percent increase in profit from a new supplier or a new client. We also asked them about the number of hours they spend each month searching for suppliers and clients. And we asked them a set of questions about personal initiative, borrowed from Campos, Frese, Goldstein, Iacovone, Johnson, McKenzie and Mensmann (2017), which might measure the extent to which they take initiative in establishing new partnerships.

Table 9 reports the results. Among suppliers (Panel A), columns 1 and 2 show a significant increase in firms' expected profit gain from a new client, as well as a significant increase in the amount of time they spend searching for new clients. Columns 3 and 4 show no analogous increases in beliefs or search for suppliers, consistent with the fact that these firms were referred clients, not suppliers. Column 5 shows a significant increase in personal initiative. Finally, column 6 shows a significant increase in the number of their non-referred partners, measured as the total number of partners they reported in the firm survey minus the number of referred partners with whom they reported a transaction in the network survey.

Among clients (Panel B), we find a significant impact on the beliefs about and time allocated to searching for suppliers. We find no impacts on beliefs or search for clients, consistent with the fact that these firms were referred suppliers, not clients. There is a positive but insignificant increase in the number of non-referred partner. Appendix Table A15 shows that in the growth-oriented subsample these results are stronger, and the impact on non-referred partners is highly significant.

These results support the narrative that in response to the referrals, firms increased their beliefs about the benefits of search, allocated more time to search, and established additional new partnerships beyond the ones we referred to them. These results are consistent with our finding in Section 2.1 that firms underestimated the satisfaction from referrals, and provide direct evidence that firms under-searched because they undervalued partners. Thus, our results identify a new mechanism, undervaluation of potential partners, which acts as both a matching friction and a search friction in firm-to-firm access. This mechanism has potentially different implications from the more commonly emphasized information friction mechanism. In settings where undervaluation is important, providing credible evidence on partner quality (which we achieved using the subsidies) may be an essential component to effective interventions; merely reducing search costs, as shown by the information referrals, may not work.

It is natural to ask how undervaluation can persist in our setting featuring spatially concentrated firms and a centralized market. A plausible answer is that undervaluation discourages search—even if that search is not too costly—and hence prevents firms from updating their false beliefs, leading to a self-confirming equilibrium (Fudenberg and Levine 1993, Schwartzstein 2014). In fact, undervaluation may often be a natural state of affairs: a firm overvaluing partners will search and thus eventually form well-calibrated beliefs, but a firm undervaluing partners will not and thus will maintain pessimistic beliefs. Although we document the undervaluation mechanism in the context of firm-to-firm access, this argument suggests that it may prevent the adoption of best practices more broadly, and indeed it has been documented in labor search as well (Jäger et al. 2024).

These results suggest that the impacts on firm performance may have been partly driven not by the referrals we made, but by other partnerships obtained because of increased search. This indirect effect may help explain the large treatment effects, and suggests that our intervention, by changing search attitudes, may have generated large private and social returns.[23]

3.4 Return to capital

We turn to estimate private and social returns by comparing the gains from the referrals with the cost of the intervention.

Private return. Given the fact that the information referrals resulted in no take-up, while the subsidized referrals did, a natural notion of the private return is the profit gain from the subsidized referrals relative to the cost of the subsidy. Firms in the information treatment could have earned that return by self-financing the subsidy.

We calculate this return separately for suppliers and for clients. For suppliers, we compute the annual aggregate profit gain to treated suppliers as the product of the profit effect from column 2 of Table 6 and the number of suppliers, and compare it to the total subsidy cost we paid out. The annual profit gain is about 8 times the subsidy cost. For clients, we focus on growth-oriented pen-brush producers, and compute the aggregate profit gain to treated clients in this subgroup as the product of the profit effect from column 2 of Table 7 and the number of firms in this subgroup. Comparing this gain with the total subsidy cost we paid out (to all firms not just in this subgroup), we find that the annual profit gain is about 17 times the cost of the subsidy. Adding up across suppliers and clients, the total profit to treated firms is about 25 times the cost of the subsidy, corresponding to an annual return of 2,500 percent.

These returns are very high. To put them in perspective, note that existing estimates of the private return to capital in firms in the development context are on the order of 100 percent per year (De Mel, McKenzie and Woodruff 2008, Banerjee and Duflo 2014, Cai and Szeidl 2024). The returns we estimate here are an order of magnitude larger. These results provide further evidence

[23] This logic also highlights the potential confound that these impacts on search and partnering may interfere with our treatment effect evaluation. For example, if treated clients create new partnerships, that impacts the performance of their new suppliers. But given the random treatment assignment, treated clients should search treated and untreated suppliers with the same intensity. Thus, to a first approximation, this impact on suppliers should be balanced and should not affect the treatment effect estimate. However, if this force is important, then we underestimate the social return from the referrals.

that the barrier to taking up the information referral was not a realistic cost-benefit calculation.

Social return. The private return does not reflect the social return for three main reasons. First, it only captures the gains in producer surplus, but ignores the gains in consumer surplus accumulating to the final good consumer. After all, the increased revenue of treated clients must reflect consumers' choice to spend more on the products of these firms, implying through revealed preference that these consumers are better off. Second, the private return ignores business stealing effects which potentially lower the aggregate producer surplus. Third, it ignores the cost of collecting the firm and network data used to create the referrals.

We turn to account for these effects. To incorporate the consumer surplus, we build on Cai and Szeidl (2024) and in Appendix B derive an expression for the gain in the consumer surplus under a CES demand system, which is valid even in the presence of business stealing effects in the final goods market. We can apply this formula for client firms. The gain in consumer surplus, to a first-order approximation, is predicted to be

$$\Delta CS \approx \frac{\beta_C^R}{\sigma - 1} \cdot \sum_{j:T_j=1} R_j. \tag{5}$$

Here β_C^R is the impact of the treatment on log client revenue, R_j is the revenue of client firm j absent the intervention, T_j is the treatment status of the firm, and σ is the elasticity of substitution in the final goods market. Intuitively, the revenue gain in treated firms (β_C^R times the sum) is a measure of demand reallocation which reflects the revealed preference of the consumer. But how that measure maps into the consumer surplus depends on how substitutable products are: with high substitutability, the same revenue gain reflects a smaller gain in consumer surplus. Following Cai and Szeidl (2024) we use this formula with $\sigma = 5$, which is a conservative choice given recent estimates of the retail elasticity of substitution, such as Atkin, Faber and Gonzalez-Navarro (2018) who find σ in the range of 2.3-4.4, and Dolfen, Einav, Klenow, Klopack, Levin, Levin and Best (2019) who find σ in the range of 4.3-6.1.

To estimate the producer surplus, we note that—as discussed in Section 3.2—exposure regressions yield no evidence of business stealing in either the intermediate good or the final good market. We thus assume that the profit gains accurately reflect the gains in the producer surplus, and compute these profit gains the same was as for the private return. Finally, we compute returns relative to the total cost of conducting the intervention, including both the subsidy and the survey costs.

We find that the annual gain in consumer surplus was about 3.39 times the cost of the intervention. The annual gain in producer surplus for clients was 5.91 times the cost of the intervention and for suppliers 4.23 times the cost of the intervention. Thus, we estimate the annual social return to be approximately 1,350 percent. We conclude that the intervention generated very large welfare gains, highlighting the potential benefits from policies improving firm-to-firm market access.

4 Marketing offer intervention

Given the importance of matching frictions in our context—preventing take-up in the information referrals—a natural question is whether there are cheaper ways than offering a subsidy to eliminate those frictions. Recall from Section 2.1 that our survey of firms participating in the information referrals suggested two types of matching frictions: (i) undervaluation and (ii) lack of marketing skills. In a small-scale follow-up experiment in 2023 we evaluated a new way to make a screened referral: by producing a marketing offer on behalf of the supplier and taking it to the buyer. This marketing offer was a one-page document providing information about the supplier such as the type and price of its product, in combination with a free sample produced by the supplier if one was available. We worked with the supplier to prepare this offer and then sent it to the client. This intervention was expected to overcome the undervaluation problem by providing verifiable information about product quality via the free sample, and overcome the lack of marketing skills by contacting the client on behalf of the supplier.

We implemented the marketing offer treatment in the sample of T0-to-T0 candidate screened referrals. We had two treatment arms.

- EI: Enhanced information. In addition to the information we provided in the information treatment arm of the main experiment, we explained to the firms that the proposed partner would likely be a good match because similar referrals to other firms led to subsequent trades, and we encouraged them to contact the proposed partner.

- MO: Marketing offer. In addition to EI, we administered the marketing offer as described above.

We offered these treatments as follows. Recall that in our main intervention for each T0 client we constructed two candidate screened referrals. We used this sample of referrals, including the information referrals because they did not lead to subsequent transactions. For a random third of client firms, we administered the enhanced information treatment to both of their screened referrals. For the remaining two-thirds of client firms, we administered the marketing offer to one of their screened referrals (the A referral in Figure 2), and the enhanced information treatment to the other (the B referral). This design allows us to evaluate learning effects. Indeed, undervaluation suggests that once beliefs are recalibrated, the firm should contact other referred partners, while lack of marketing skills suggests that once the supplier learns the marketing technology, it should use it to contact other referred partners.

We use the following estimating equation:

$$\begin{aligned} y_{ij} = \delta_M \cdot \textit{Marketing Offer}_{ij} + \delta_C \cdot \textit{Client Indirect}_{ij} + \delta_S \cdot \textit{Supplier Indirect}_{ij} \\ + \textit{Supplier referral degree f.e.} + \textit{Business type f.e.} + \varepsilon_{ij}. \end{aligned} \tag{6}$$

This is a link-level regression in the sample of all T0-to-T0 screened referrals. The outcome is a measure of transactions. On the right hand side, the main treatment variable is an indicator for the link receiving a marketing offer. We also include an indicator for whether the client in the link received another marketing offer (from its other screened referral), which measures the opportunity for the client to learn about the value of the referrals. Given the design, this measure is effectively randomly assigned. Analogously, we include an indicator for whether the supplier in the link "sent" another marketing offer to a different client(more precisely, we worked with them to prepare and send the offer). This measures the opportunity for the supplier to learn, either about the value of referrals or about how to create a marketing offer. The random treatment assignment creates random variation in this variable as well, but it is not purely random since a supplier with more candidate screened referrals is more likely to have the opportunity to learn. To isolate the random variation, we control for indicators for the number of screened referrals the supplier has.

Table 10: Marketing offer intervention

Dep. Var.:	Link	Num Transactions	Value (RMB)	Link	Num Transactions	Value (RMB)
	(1)	(2)	(3)	(4)	(5)	(6)
Marketing Offer * Growth-oriented brush pen producer				0.500***	1.334***	2,655.323***
				(0.112)	(0.329)	(655.081)
Client Indirect * Growth-oriented brush pen producer				0.279**	0.426	713.997
				(0.111)	(0.327)	(652.173)
Marketing Offer	0.191***	0.457**	791.613**	0.015	-0.008	-140.195
	(0.063)	(0.181)	(358.221)	(0.074)	(0.217)	(431.780)
Client Indirect	0.077	0.126	130.973	-0.026	-0.047	-177.364
	(0.060)	(0.171)	(338.328)	(0.071)	(0.210)	(418.037)
Supplier Indirect	0.141*	0.287	526.271	0.131*	0.241	426.070
	(0.081)	(0.231)	(457.996)	(0.074)	(0.218)	(434.763)
Growth-oriented brush pen producer				0.006	0.022	-11.848
				(0.078)	(0.228)	(455.033)
Indicators num times supplier referred	Yes	Yes	Yes	Yes	Yes	Yes
Business type FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	218	218	218	218	218	218

Notes: Sample is referred links in the control group of the main experiment, i.e., hypothetical referrals. Client indirect is an indicator for an information referral where the client received a marketing offer on another referral; Supplier indirect is defined analogously for suppliers. Indicators for the number of times a supplier has been referred are included. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table 10 reports the results. Column 1 shows that the marketing offer increased the probability of a subsequent transaction by a significant 21 percentage points. Columns 2 and 3 show that it also significantly increased the number of transactions and the transaction value. In column 1, the indirect effect to the other referred links of the supplier is positive and significant at the 10 percent level. In columns 1-3 the indirect effect on the client side is insignificant. In columns 4-6 we use interactions to zoom in on the subgroup of growth-oriented brush pen producers. Consistent with our main results that referrals work for these types of clients, in this subgroup the direct effect of the marketing offer is several times larger and more significant. Column 4 shows that in this subgroup the client-side indirect effect on link creation is also significant.

The direct effects show that the marketing offer succeeded in converting referrals into transactions. The indirect effects, although more noisily estimated, suggest learning by both suppliers and clients. This learning sheds some light on the two matching frictions highlighted above, undervaluation and lack of marketing skills. The learning on the supplier side can be consistent with either type of friction constraining suppliers: the marketing offer may have improved their valuation and may have provided them with a new marketing technology. The learning on the client side is plausibly evidence for undervaluation constraining clients, since clients did not acquire a new technology.

To gauge the magnitude of marketing offer's direct effect we compare it to the effect of the subsidized referral from our main intervention. A direct comparison with Table 3 is complicated by the fact that in the main intervention we evaluated impacts over a year, whereas here only over 4 months. Therefore, we re-estimated Table 3 for a four-month horizon (not reported), which was possible because in the follow-up surveys we asked firms about transactions at that horizon as well. We find that the marketing offer was about 51 percent as effective in creating a new transaction, created about 39 percent as many transactions, and these transactions had about 30 percent as high total value as the subsidy. Thus, the marketing offer appears to be at least 30 percent as effective as the subsidy. But it comes at an estimated cost of only 0.5 percent of the subsidy. Thus, after search frictions are eliminated, the marketing offer is about 60 times as effective as the subsidy. This result suggests that improving the design of market access interventions can generate further gains.

5 Conclusion

We have estimated the impact of firm-to-firm referrals on business networks and performance. We believe that our results support the following narrative.

1. Firms underestimate the benefit of new partners and do not search.
2. The referrals create new partnerships and crowd out some existing ones, improving firms' overall satisfaction with partners.
3. The referrals greatly improve firms' business performance, due to two main mechanisms.
   (a) Suppliers upgrade quality and clients upgrade variety in a complementary fashion.

(b) Firms increase their beliefs about the value of partners and their search effort.

4. The resulting private and social gains are very large relative to the cost of the referrals, in part because by changing beliefs, the intervention affected not just decisions about the referred partners but also subsequent decisions.

This narrative suggests that frictions in firm-to-firm access are an important growth barrier, and that policies eliminating this barrier can generate large gains.

A key question is to what extent our results generalize to other contexts. An important characteristic of our context is that there is substantial product differentiation, which makes the choice of partners important. However, product differentiation seems common across much of manufacturing. Conditional on the industry being differentiated, we think that in our setting, many frictions in firm-to-firm access are actually low. Firms are based in a single county, have been active in the industry for over two decades, and have access to a centralized market. Thus, information about the identity of potential partners should be easy to obtain. Despite these features we find large effects. In other settings, in which firms are more dispersed, the industry features higher turnover, and firm-to-firm markets are less centralized, access frictions may be even larger.

Our main policy implication is that improving firm-to-firm access can generate large societal gains. Our results also hold insights about how to design such policies. The undervaluation friction suggests that policies can be enhanced if they enable access to information about partner quality. The marketing offer result suggests that there may be cost-effective ways to achieve that goal. And our findings that growth-oriented clients grew more and that screened referrals had larger impacts highlight the value of targeting the right firms and perhaps even the right links.

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A Supplemental tables and figures

Table A1: Baseline Summary Statistics for Firms Remaining in 2023

	Suppliers			**Clients**		
	Untreated	Treated	Difference	Untreated	Treated	Difference
Panel A: Firm Characteristics						
Firm Age	26.317	26.642	0.325	22.273	21.376	-0.897
	(13.618)	(12.680)	(1.351)	(11.827)	(11.859)	(1.489)
Number of Employees	2.403	2.642	0.239	5.383	5.240	-0.143
	(1.665)	(2.648)	(0.228)	(5.530)	(5.292)	(0.681)
Profit (10,000 RMB)	6.519	8.791	2.271	33.039	36.782	3.743
	(9.921)	(25.011)	(1.968)	(60.405)	(64.339)	(7.844)
Sales (10,000 RMB)	14.462	16.825	2.363	73.001	80.415	7.414
	(27.366)	(38.846)	(3.463)	(125.291)	(133.540)	(16.276)
Growth Oriented	0.710	0.725	0.016	0.477	0.464	-0.013
	(0.455)	(0.447)	(0.046)	(0.501)	(0.501)	(0.063)
Panel B: Managerial Characteristics						
Gender (1=Female, 0=Male)	0.317	0.326	0.009	0.125	0.104	-0.021
	(0.467)	(0.470)	(0.048)	(0.332)	(0.306)	(0.040)
Age	53.672	53.461	-0.211	49.508	49.744	0.236
	(10.084)	(9.677)	(1.015)	(9.477)	(11.383)	(1.316)
Education- Middle School	0.457	0.466	0.009	0.672	0.728	0.056
	(0.499)	(0.500)	(0.051)	(0.471)	(0.447)	(0.058)
Panel C: Number of Partners (buyers for supplier, sellers for client)						
In Firm Data	5.591	6.808	1.217	5.813	5.456	-0.356
	(9.564)	(13.833)	(1.226)	(7.314)	(5.968)	(0.840)
In Firm Data, Winsorized at 6	3.269	3.316	0.047	3.406	3.520	0.114
	(2.358)	(2.316)	(0.240)	(2.267)	(2.320)	(0.288)
In Network Data, All Partners	2.265	2.454	0.189	3.618	3.667	0.049
	(2.780)	(3.342)	(0.316)	(3.877)	(3.871)	(0.487)
In Network Data, Supplier-client Links	1.511	1.611	0.101	2.266	2.280	0.014
	(2.461)	(2.942)	(0.279)	(3.382)	(3.383)	(0.425)
P-val of Joint Significance of Vars in Panels A-C (2023 sample)			0.990			0.986
Observations	186	193	379	128	125	253

Notes: *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Difference between screened and unscreened referrals

	(1)	(2)	(3)	(4)	(5)
Dep. Var:			If Screened Referral		
Supplier Log Sales	0.034***				
	(0.012)				
Client Log Sales	0.004				
	(0.004)				
Diff Sales Rank		0.175***			
		(0.060)			
Diff Price Rank			-0.141*		
			(0.080)		
Log Distance				-0.033**	
				(0.016)	
Kin					-0.002
					(0.070)
Business Type FE	Yes	Yes	Yes	Yes	Yes
Observations	796	799	646	805	858
R-squared	0.011	0.011	0.005	0.006	0.001

Note: Sample is all candidate referrals, screened and unscreened, made and not made. We compute sales rank for suppliers by ranking baseline (2021) sales across suppliers and normalizing the rank so that it ranges from 0 to 1. Sales rank for clients, and price rank, are computed analogously. Difference is the absolute value of the difference between suppliers and clients over the link. Standard errors clustered by supplier and client. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: Heterogeneity in link creation

Dep. Var.:	Link	Num Transactions	Value (RMB)	IHS Num Transactions	IHS Value
	(1)	(2)	(3)	(4)	(5)
Panel A					
Subsidy * Supplier log sales	0.086***	0.615***	1,502.467***	0.223***	0.855***
	(0.017)	(0.141)	(542.384)	(0.044)	(0.182)
Subsidy * Client log sales	0.041**	0.312**	970.439*	0.103**	0.400**
	(0.018)	(0.141)	(570.342)	(0.043)	(0.183)
Observations	1,586	1,586	1,586	1,586	1,586
Panel B					
Subsidy * Diff sales rank	0.034	0.874	2,903.260	0.198	0.501
	(0.102)	(0.812)	(3,250.573)	(0.255)	(1.076)
Observations	1,592	1,592	1,592	1,592	1,592
Panel C					
Subsidy * Diff price rank	-0.205**	-1.624**	-7,326.398***	-0.512**	-2.296**
	(0.100)	(0.729)	(2,714.193)	(0.238)	(0.989)
Observations	1,289	1,289	1,289	1,289	1,289
Panel D					
Subsidy * Log distance	-0.030	-0.192	-477.357	-0.082	-0.302
	(0.031)	(0.226)	(839.647)	(0.073)	(0.310)
Observations	1,499	1,499	1,499	1,499	1,499
Panel E					
Subsidy * Kin	0.247**	1.341	4,652.158	0.523**	2.510**
	(0.100)	(0.824)	(3,218.317)	(0.235)	(0.997)
Observations	1,592	1,592	1,592	1,592	1,592

Notes: Each panel in each column is a different regression. Sample is all candidate referrals, made and not made. IHS stands for inverse hyperbolic sine. Sales rank and price rank are computed the same way as in Table A2. All specifications include the uninteracted subsidy and heterogeneity-defining variable, and referral type, business type and year fixed effects. Standard errors clustered by supplier and client. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Heterogeneity in link destruction

Dep. Var.:	Link	Num Transactions	Value (RMB)	IHS Num Transactions	IHS Value
	(1)	(2)	(3)	(4)	(5)
Panel A					
Exposure * Supplier satisfactory	0.045	3.773	50,786.415*	0.526*	1.252
	(0.098)	(3.573)	(28,871.926)	(0.314)	(1.174)
Exposure * Client satisfactory	0.315***	-2.717	-15,228.832	0.432	3.065**
	(0.109)	(2.310)	(15,730.362)	(0.348)	(1.180)
Observations	646	646	646	646	646
Panel B					
Exposure * Supplier log sales	0.159***	1.906*	-3,670.175	0.406***	1.567***
	(0.029)	(1.151)	(7,667.440)	(0.089)	(0.310)
Exposure * Client log sales	0.002	-1.940	-5,860.146	-0.098	-0.090
	(0.027)	(1.196)	(3,778.696)	(0.082)	(0.289)
Observations	1,234	1,234	1,234	1,234	1,234
Panel C					
Exposure * Diff sales rank	-0.073	4.694	-4,732.430	-0.204	-1.291
	(0.214)	(6.513)	(28,531.588)	(0.602)	(2.165)
Observations	1,238	1,238	1,238	1,238	1,238
Panel D					
Exposure * Diff price rank	0.235	1.073	10,255.716	0.730	2.541
	(0.200)	(3.397)	(26,794.891)	(0.538)	(2.031)
Observations	1,044	1,044	1,044	1,044	1,044
Panel E					
Exposure * Log distance	-0.027	-0.744	7,894.447	-0.133	-0.182
	(0.043)	(0.793)	(6,360.681)	(0.120)	(0.473)
Observations	1,124	1,124	1,124	1,124	1,124
Panel F					
Exposure * Kin	0.415***	-4.408	-30,317.359	0.664*	3.822***
	(0.112)	(5.434)	(24,597.016)	(0.351)	(1.260)
Observations	1,238	1,238	1,238	1,238	1,238

Notes: Each panel in each column is a different regression. Sample is pre-existing links. IHS stands for inverse hyperbolic sine. Exposure is an indicator for the supplier, the client, or both being treated. Sales rank and price rank are computed the same way as in Table A2. All specifications include the uninteracted exposure and the heterogeneity-defining variable, and business type and year fixed effects. Standard errors clustered by supplier and client. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Main firm effects with exposure

Dep. Var.:	Log Sales	Profit (10,000 RMB)	Log Operating Cost	Log Employ-ment	Total Hrs Worked / Day	Num Reg Supplier	Num Reg Client	Satisfaction Clients / Suppliers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Suppliers								
Treatment	0.243***	1.793**	0.036	0.067*	2.656**	0.278	1.869***	0.260***
	(0.075)	(0.807)	(0.097)	(0.040)	(1.284)	(0.204)	(0.708)	(0.078)
Exposure	-0.031	1.623	0.041	0.063	2.292	0.823	1.294	-0.048
	(0.286)	(2.663)	(0.346)	(0.140)	(4.082)	(0.767)	(1.809)	(0.264)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Expected Exposure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	1.890	6.804	1.296	0.711	18.82	2.571	5.595	5.059
Observations	761	763	652	763	763	763	763	761
Panel B: Clients								
Treatment	0.036	-0.050	0.020	0.055	-0.589	1.612**	1.074	0.302***
	(0.112)	(3.795)	(0.125)	(0.066)	(3.787)	(0.672)	(1.796)	(0.085)
Exposure	0.268	30.715*	0.132	0.575**	37.652**	0.913	8.463	0.025
	(0.367)	(16.437)	(0.453)	(0.242)	(14.721)	(2.576)	(8.919)	(0.299)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Expected Exposure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	3.340	37.38	2.740	1.349	39.78	6.102	15.74	5.308
Observations	520	520	502	520	520	520	520	496

Notes: Sample in Panel A is suppliers, in Panel B is clients. Exposure is share of partners, clients in Panel A and suppliers in Panel B, which are treated. Expected exposure is computed across realizations of the randomization. Indicator for firm having no regular partners (clients in Panel A and suppliers in Panel B) is always included. Otherwise Table is analogous to Table 7. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Client firm exposure by growth orientation

Dep. Var.:	Log Sales	Profit (10,000 RMB)	Log Operating Cost	Log Employ-ment	Total Hrs Worked / Day	Num Reg Supplier	Num Reg Client	Satisfaction Suppliers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Growth-oriented brush pen producers								
Treatment	0.419**	7.722*	0.510***	0.218**	7.453*	2.680***	2.803	0.377**
	(0.179)	(4.204)	(0.186)	(0.098)	(3.801)	(0.868)	(2.068)	(0.145)
Exposure	0.438	14.937	0.348	0.656*	35.039*	-3.194	-6.098	0.024
	(0.455)	(13.669)	(0.577)	(0.386)	(20.495)	(3.600)	(11.726)	(0.469)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Expected Exposure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	2.735	22.48	2.075	1.091	28.24	5.020	12.49	4.889
Observations	202	202	191	202	202	202	202	187
Panel B: Not growth-oriented brush pen producers								
Treatment	-0.063	0.181	-0.180	-0.017	2.238	1.789	1.344	0.222*
	(0.184)	(7.855)	(0.201)	(0.108)	(7.248)	(1.428)	(3.868)	(0.129)
Exposure	0.482	57.162	0.219	0.413	35.835	4.704	25.668**	-0.369
	(0.663)	(35.187)	(0.778)	(0.304)	(23.917)	(3.099)	(11.426)	(0.448)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Expected Exposure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	3.877	50.91	3.282	1.483	49.32	7.754	21.28	5.766
Observations	214	214	211	214	214	214	214	209

Notes: Regressions in subsamples of client firms. Sample in panel A is growth-oriented brush pen producers, in Panel B is non-growth-oriented brush pen producers. Exposure is share of suppliers which are treated. Expected exposure is computed across realizations of the randomization. Indicator for firm having no regular suppliers is always included. Otherwise Table is analogous to Table 8. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Main firm effects with exposure of close competitor

Dep. Var.:	Log Sales	Profit (10,000 RMB)	Log Operating Cost	Log Employ-ment	Total Hrs Worked / Day	Num Reg Supplier	Num Reg Client	Satisfaction Clients / Suppliers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Suppliers								
Treatment	0.246***	1.655*	0.042	0.078*	2.907*	0.397*	2.040**	0.203***
	(0.078)	(0.929)	(0.103)	(0.041)	(1.480)	(0.211)	(0.847)	(0.066)
Share of Treated	-0.055	2.187	-0.244	0.202	4.105	0.529	3.233	-0.317
among Close Competitor	(0.272)	(2.935)	(0.377)	(0.142)	(4.149)	(0.739)	(2.617)	(0.236)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	1.890	6.804	1.296	0.711	18.82	2.571	5.595	5.059
Observations	755	757	646	757	757	757	757	755
Panel B: Clients								
Treatment	0.024	-0.378	-0.006	0.049	-0.843	1.593**	0.683	0.234***
	(0.113)	(3.911)	(0.122)	(0.068)	(3.894)	(0.685)	(1.863)	(0.071)
Share of Treated	0.007	13.735	0.050	0.074	7.619	2.468	0.182	0.195
among Close Competitor	(0.309)	(10.476)	(0.419)	(0.190)	(9.994)	(2.439)	(5.391)	(0.222)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	3.340	37.38	2.740	1.349	39.78	6.102	15.74	5.308
Observations	514	514	496	514	514	514	514	491

Notes: Sample in Panel A is suppliers, in Panel B is clients. In columns 2, 6 and 7 outcome is winsorized at the 99th percentile in each sample, in column 8 satisfaction is with clients in Panel A and with suppliers in Panel B, and is standardized. Baseline value of the outcome variable is included when available, not in column 5 because we did not collect that variable at baseline. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Main client firm effects with exposure of close competitor

Dep. Var.:	Log Sales	Profit (10,000 RMB)	Log Operating Cost	Log Employ-ment	Total Hrs Worked / Day	Num Reg Supplier	Num Reg Client	Satisfaction Suppliers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Growth-oriented brush pen producers								
Treatment	0.392**	6.765*	0.475***	0.239**	9.364**	2.706***	2.386	0.258**
	(0.178)	(3.790)	(0.180)	(0.106)	(4.264)	(0.822)	(1.902)	(0.108)
Share of Treated	0.294	30.137*	0.643	0.121	14.656	3.744	2.979	0.472
among Close Competitor	(0.502)	(16.240)	(0.506)	(0.311)	(15.814)	(3.953)	(5.412)	(0.350)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	2.735	22.48	2.075	1.091	28.24	5.020	12.49	4.889
Observations	200	200	189	200	200	200	200	185
Panel B: Not growth-oriented brush pen producers								
Treatment	-0.045	-1.694	-0.157	-0.005	1.272	1.398	-0.663	0.190*
	(0.179)	(7.867)	(0.189)	(0.113)	(7.217)	(1.346)	(3.920)	(0.106)
Share of Treated	-0.205	16.498	-0.266	0.082	15.871	1.715	-0.583	0.254
among Close Competitor	(0.458)	(13.976)	(0.570)	(0.264)	(15.431)	(4.289)	(11.583)	(0.316)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	3.877	50.91	3.282	1.483	49.32	7.754	21.28	5.766
Observations	210	210	207	210	210	210	210	206

Notes: Regressions in subsamples of client firms. Sample in panel A is growth-oriented brush pen producers, in Panel B is non-growth-oriented brush pen producers. In columns 2, 6 and 7 outcome is winsorized at the 99th percentile in each sample, in column 8 satisfaction is with suppliers and is standardized. Baseline value of the outcome variable is included when available, not in column 5 because we did not collect that variable at baseline. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Firm self-reported growth performance on 1-5 scale

Dep. Var.:	Perceived # Products (1-5)	Perceived Quantity (1-5)	Perceived Avg Quality (1-5)	Perceived Avg Price (1-5)	Perceived Sales (1-5)	Perceived Profits (1-5)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Suppliers						
Treatment	0.194*	0.202*	0.280***	0.179*	0.240**	0.348***
	(0.108)	(0.108)	(0.086)	(0.092)	(0.110)	(0.120)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	2.261	2.254	2.944	2.761	2.254	2.190
Observations	288	288	288	288	288	288
Panel B: Clients						
Treatment	0.242	0.203	0.192**	0.154*	0.323*	0.286*
	(0.165)	(0.162)	(0.085)	(0.091)	(0.166)	(0.162)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	2.375	2.362	3.038	2.813	2.350	2.337
Observations	160	160	160	160	160	160

Notes: Sample in Panel A is suppliers, in Panel B is clients. All outcomes collected in 2024 phone survey and measure perceived business performance since 2020 on a 5-point scale. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Experimenter demand

	Owner's Phone Use		Enumerator Observation in the Field				
Dep. Var.:	Monthly Bill (RMB)	Num Calls & Wechat / Month	Num Visitors	Num Calls	Busy (1-5)	Num Employees	Assessment of operations (1-5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Suppliers							
Treatment	10.263**	3.495**	0.031	0.094**	0.302**	0.351	0.310***
	(5.073)	(1.454)	(0.041)	(0.041)	(0.120)	(0.225)	(0.103)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	74.19	14.04	0.06	0.10	2.36	0.60	2.38
Observations	373	373	363	363	369	363	371
Panel B: Clients							
Treatment	11.320	2.427	-0.023	0.068	0.232	0.212	0.166
	(7.840)	(2.478)	(0.068)	(0.060)	(0.146)	(0.161)	(0.125)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	102.35	21.13	0.15	0.10	2.78	0.65	2.98
Observations	251	251	246	247	250	246	251

Notes: All outcomes collected in 2023 survey. Columns 3-7 are enumerators' evaluation of the firm. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A11: Clients: experimenter demand by growth orientation

	Owner's Phone Use		Enumerator Observation in the Field				
Dep. Var.:	Monthly Bill (RMB)	Num Calls & Wechat / Month	Num Visitors	Num Calls	Busy (1-5)	Num Employees	Assessment of operations (1-5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Growth-oriented brush pen producers							
Treatment	9.175	1.870	-0.040	0.073	0.543**	0.367*	0.371*
	(11.619)	(4.905)	(0.120)	(0.117)	(0.217)	(0.204)	(0.197)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	101.88	24.11	0.11	0.16	2.69	0.63	2.91
Observations	95	95	95	95	95	95	95
Panel B: Not growth-oriented brush pen producers							
Treatment	5.009	6.392	-0.137	0.002	-0.147	0.058	-0.220
	(12.632)	(4.060)	(0.113)	(0.086)	(0.250)	(0.258)	(0.213)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	117.4	23.17	0.17	0.13	3.16	0.76	3.30
Observations	101	101	99	100	101	99	101

Notes: All outcomes collected in 2023 survey. Columns 3-7 are enumerators' evaluation of the firm. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A12: Performance over time

Dep. Var.:	Log Sales	Profit (10,000 RMB)	Log Operating Cost	Log Employ-ment	Total Hrs Worked / Day	Num Reg Supplier	Num Reg Client	Satisfaction Clients / Suppliers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Suppliers								
Treatment	0.205**	1.254*	0.104	0.071	3.884**	0.276	1.948**	0.256***
	(0.088)	(0.741)	(0.109)	(0.049)	(1.714)	(0.270)	(0.849)	(0.093)
Treatment* 2023	0.077	0.497	-0.108	-0.007	-2.399	0.196	-0.145	-0.075
	(0.104)	(1.373)	(0.148)	(0.063)	(1.699)	(0.406)	(1.028)	(0.123)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	1.890	6.804	1.296	0.711	18.82	2.571	5.595	5.059
Observations	761	763	652	763	763	763	763	761
Panel B: Clients								
Treatment	0.092	0.300	0.017	0.109	-0.992	2.176**	1.394	0.183*
	(0.141)	(4.950)	(0.144)	(0.089)	(5.115)	(1.005)	(2.750)	(0.098)
Treatment* 2023	-0.103	-0.304	0.012	-0.120	0.069	-1.168	-1.039	0.119
	(0.169)	(6.563)	(0.209)	(0.106)	(5.213)	(1.187)	(3.713)	(0.142)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	3.340	37.38	2.740	1.349	39.78	6.102	15.74	5.308
Observations	520	520	502	520	520	520	520	496

Notes: Sample in Panel A is suppliers, in Panel B is clients. In columns 2, 6 and 7 outcome is winsorized at the 99th percentile in each sample, in column 8 satisfaction is with clients in Panel A and with suppliers in Panel B, and is standardized. Baseline value of the outcome variable is included when available, not in column 5 because we did not collect that variable at baseline. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A13: Clients: performance over time by growth orientation

Dep. Var.:	Log Sales	Profit (10,000 RMB)	Log Operating Cost	Log Employ-ment	Total Hrs Worked / Day	Num Reg Supplier	Num Reg Client	Satisfaction Clients / Suppliers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Growth-oriented brush pen producers								
Treatment	0.501**	8.031	0.438**	0.325**	10.791*	3.532***	3.247	0.114
	(0.232)	(5.504)	(0.203)	(0.139)	(6.295)	(1.174)	(3.117)	(0.162)
Treatment* 2023	-0.155	0.729	0.134	-0.190	-4.599	-1.826	-0.872	0.258
	(0.257)	(5.894)	(0.338)	(0.167)	(6.674)	(1.642)	(3.738)	(0.242)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	2.735	22.48	2.075	1.091	28.24	5.020	12.49	4.889
Observations	202	202	191	202	202	202	202	187
Panel B: Not growth-oriented brush pen producers								
Treatment	0.018	1.323	-0.077	0.097	0.524	2.110	1.695	0.171
	(0.222)	(9.964)	(0.247)	(0.147)	(9.169)	(2.008)	(5.885)	(0.148)
Treatment* 2023	-0.130	-5.732	-0.145	-0.199	2.327	-1.298	-4.797	0.067
	(0.305)	(14.760)	(0.341)	(0.180)	(9.915)	(2.249)	(7.610)	(0.230)
Baseline Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	3.877	50.91	3.282	1.483	49.32	7.754	21.28	5.766
Observations	214	214	211	214	214	214	214	209

Notes: Regressions in subsamples of client firms. Sample in panel A is growth-oriented brush pen producers, in Panel B is non-growth-oriented brush pen producers. In columns 2, 6 and 7 outcome is winsorized at the 99th percentile in each sample, in column 8 satisfaction is with suppliers and is standardized. Baseline value of the outcome variable is included when available, not in column 5 because we did not collect that variable at baseline. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A14: Clients: upgrading by growth orientation

Dep. Var.:	Quality score first product			Quality check	If 2nd	Share 2nd	Avg Log
	Craftsmanship	Durability	Total	hrs/wk	product	product	Price
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Growth-oriented brush pen producers							
Treatment	0.335*	0.111	0.195	3.282**	0.125*	6.045**	0.285*
	(0.177)	(0.215)	(0.196)	(1.431)	(0.064)	(2.597)	(0.170)
Baseline Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	-0.529	-0.549	-0.555	5.873	0.804	22.94	1.727
Observations	133	133	133	202	202	201	188
Panel B: Not growth-oriented brush pen producers							
Treatment	-0.131	-0.284	-0.230	3.574*	-0.006	4.592*	-0.042
	(0.177)	(0.197)	(0.185)	(1.822)	(0.046)	(2.483)	(0.185)
Baseline Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	-0.181	-0.241	-0.229	5.921	0.842	22.27	1.897
Observations	156	156	156	214	214	213	209

Notes: Quality score in columns 1-3 is evaluated by experts, residualized by product type and standardized. In column 7 average log price is the average of the log prices of the firm's main products we collect data on, up to three. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A15: Clients: search by growth orientation

Dep. Var.:	Perceived profit growth if new client %	Search new clients hrs/month	Perceived profit growth if new supplier %	Search new suppliers hrs/month	Personal initiative	Num non-referred partners
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Growth-oriented brush pen producers						
Treatment	0.709	-1.493	3.390**	4.420*	0.264*	2.755***
	(2.348)	(2.510)	(1.403)	(2.540)	(0.153)	(0.842)
Baseline Control, Year FE						Yes
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	5.55	7.16	1.85	2.62	3.83	5.020
Observations	95	95	95	95	95	202
Panel B: Not growth-oriented brush pen producers						
Treatment	-0.754	3.616	2.575*	2.116	0.039	0.349
	(2.125)	(3.762)	(1.417)	(1.972)	(0.152)	(3.286)
Baseline Control, Year FE						Yes
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	7.62	10.11	2.92	3.15	4.00	8.105
Observations	101	101	101	101	101	214

Notes: Outcomes in columns 1-5 collected in the 2023 survey. Outcome in column 5 is averge response to seven questions on personal initiative. Outcome in column 6 is number of partners (clients in Panel A, suppliers in Panel B) reported in the firm data minus number of referred partners reported in the network data. Standard errors clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A16: Summary statistics of second-phase experiment

	Clients		
	Non-Marketing Offer	Marketing Offer	Difference
Panel A: Firm Characteristics			
Firm Age	25.550	24.119	-1.431
	(12.077)	(11.645)	(2.264)
Number of Employees	4.425	4.988	0.563
	(5.560)	(5.628)	(1.077)
Profit (10,000 RMB)	29.313	22.910	-6.403
	(64.566)	(42.580)	(9.731)
Sales (10,000 RMB)	63.967	62.615	-1.353
	(135.737)	(120.040)	(24.066)
Panel B: Managerial Characteristics			
Gender (1=Female, 0=Male)	0.100	0.131	0.031
	(0.304)	(0.339)	(0.063)
Age	52.475	51.298	-1.177
	(10.188)	(9.076)	(1.815)
Education- Middle School	0.700	0.655	-0.045
	(0.464)	(0.478)	(0.091)
Panel C: Number of Partners (buyers for supplier, sellers for client)			
In Firm Data	5.975	5.607	-0.368
	(6.670)	(5.678)	(1.155)
In Firm Data, Winsorized at 6	3.475	3.714	0.239
	(2.136)	(2.171)	(0.415)
In Network Data, Supplier-client Links	1.950	2.012	0.062
	(2.679)	(2.877)	(0.541)
Observations	40	84	124

Notes: *** p<0.01, ** p<0.05, * p<0.1.

B Consumer surplus evaluation

Setup. We model only client firms. We assume there is a continuum of such firms of some fixed positive mass and index them by $\in J$. Their output combines into a composite good

$$Q_J = \left[\int_{j \in J} (h_j \cdot Q_j)^{1-1/\sigma} dj\right]^{\frac{\sigma}{\sigma-1}} \tag{7}$$

where h_j is the quality or appeal of the product (or service) of firm j.

Consumer utility is

$$\frac{Q_J^\theta}{\theta} + H \tag{8}$$

where $0 < \theta < 1$ and H is a numeraire good with price normalized to one.

In the model, firm j has productivity ω_j and uses a single input that has unit price. Thus, we can treat the price of the firm as exogenous. The treatment increases h_j for treated firms by a factor γ, so that $\log h_j = \log \tilde{h}_j + \gamma T_j$. We can think of this as a reduced-form representation of the idea that client firm j is referred a new supplier that produces a higher-quality input, and thus is able to produce a a second higher-quality product. We capture this second product in a simple way by assuming that the firm's overall product quality increases.

Model solution. Maximizing (7) subject to the budget constraint $\int_{j \in J} P_j Q_j dj = E$ implies

$$Q_j = Q_J h_j^{\sigma-1} P_j^{-\sigma} \lambda^{-\sigma}$$

for $j \in J$ where λ is the multiplier on the constraint. Expressing $(h_j Q_j)^{1-1/\sigma}$ from this and integrating over j gives

$$\frac{1}{\lambda} = \left(\int_{j \in J} \left(\frac{P_j}{h_j}\right)^{1-\sigma} dj\right)^{\frac{1}{1-\sigma}}$$

which is the quality-adjusted price index and which we denote by P_J. It then follows directly that

$$\frac{h_j Q_j}{Q_J} = \left(\frac{P_j / h_j}{P_J}\right)^{-\sigma} \tag{9}$$

for $j \in J$ so that the quality-adjusted relative quantity relates with elasticity $-\sigma$ to the quality-adjusted relative price of a product. Rearranging this implies that $\int_{j \in J} P_j Q_j dj = P_J Q_J$, justifying our definition of P_J.

Given a total budget B, maximizing (8) subject to $H + P_J Q_J = B$ yields

$$Q_J^{\theta-1} = P_J \tag{10}$$

which implies that

$$P_J Q_J = Q_J^{\theta} = P_J^{\frac{\theta}{\theta-1}}$$

and that total utility is

$$\frac{1-\theta}{\theta} P_J^{\frac{\theta}{\theta-1}} + B. \tag{11}$$

We define the consumer surplus as the first term and the producer surplus as the second term in this expression.

Mapping to evidence. The revenue of firm j is

$$P_j Q_j = P_J Q_J \left(\frac{P_j}{h_j}\right)^{1-\sigma} P_J^{\sigma-1} = P_J^{\frac{\theta}{\theta-1}+\sigma-1} \left(\frac{P_j}{h_j}\right)^{1-\sigma} \tag{12}$$

which means that we can write log revenue in the cross section as

$$\log P_j Q_j = const + (\sigma - 1)\gamma T_j + \varepsilon_j \tag{13}$$

where T_j is orthogonal to ε_j. We can interpret this equation as a regression of log revenue on the treatment, in which the regression coefficient equals $\beta = \gamma(\sigma - 1)$. The empirical analogue of this equation is the revenue regression in the sample of growth-oriented brush pen producers, Column 1 in Table 7.

Welfare effect. The impact of the treatment on the consumer surplus, for γ small, equals the change in the consumer surplus in response to a change in γ from zero to positive. The derivative of (11) with respect to γ, holding fixed E,

$$-P_J^{\frac{1}{\theta-1}} \frac{1}{1-\sigma} P_J^{\sigma}(1-\sigma) \int_{J:T_j=1} \left(\frac{P_j}{h_j}\right)^{1-\sigma} = -P_J^{\frac{\theta}{\theta-1}} P_J^{\sigma-1} \int_{J:T_j=1} \left(\frac{P_j}{h_j}\right)^{1-\sigma} = \int_{j:T_j=1} P_j Q_j.$$

Thus, to a first-order approximation in γ, the change in the consumer surplus as a result of the treatment is

$$\Delta CS = \gamma \int_{j:T_j=1} P_j Q_j = \frac{\beta}{\sigma - 1} \int_{j:T_j=1} P_j Q_j. \tag{14}$$

This concludes the formal derivation of (5).

C The Brush Pen: Production and Quality Evaluation

This appendix provides more details about the brush pen and especially about the quality evaluation procedure.

C.1 The Product and Production

We include some pictures of the product and the production process.

Figure A1: Brush pens of various sizes and types of hairs

Figure A2: Workshop for brush head production

Figure A3: Workshop for handle production

Figure A4: Stores for brush head and handle

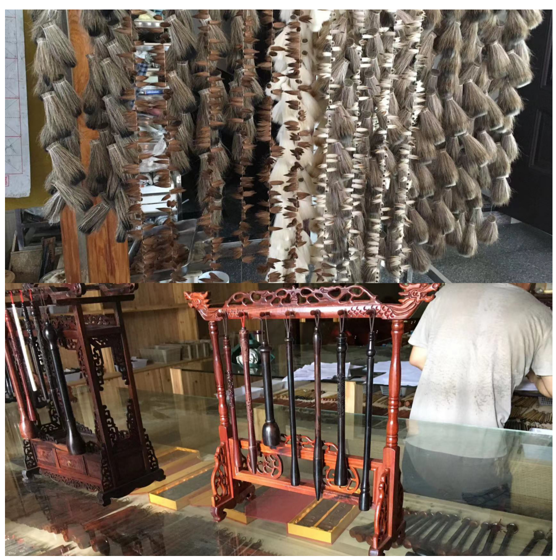


Figure A5: Assembling and store for brush pen

C.2 Brush Pen Structure

The brush pen is divided into five main components, each with specific dimensions:

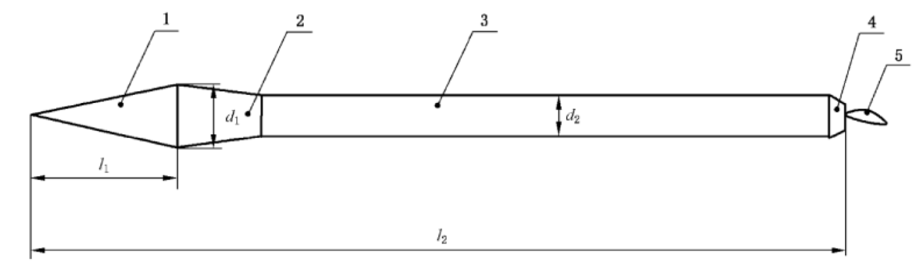
1. **Brush head top**: The working end of the brush pen that comes into contact with the writing surface.
2. **Ferrule**: The section that holds the brush head in place and connects it to the handle.
3. **Handle**: The main body of the brush pen, providing grip and balance.
4. **End Cap**: The cap at the end of the handle, often used for aesthetic and functional purposes.
5. **Pen Loop**: A loop for hanging or attaching the brush pen.

Key measurements include:

- l_1: Length of exposed brush head, important for determining the precision and flexibility of the brush.

- l_2: Total length of the brush pen, affecting the overall balance and handling.
- d_1: Diameter of the brush head, influencing the fineness of the strokes.
- d_2: Diameter of the handle, impacting the comfort and grip.

Figure A6: Structure of pen



C.3 Evaluation Criteria

C.3.1 Brush Head Quality

1. **Classification of Brush Head Types**
   - Mixed Hair Brush: Combines different types of animal hair.
   - Goat Hair Brush: Made entirely from goat hair.
   - Weasel Hair Brush: Made entirely from weasel hair.
2. **Grading of Brush Head Quality**
   - The classification criteria are based on:
     (a) Fineness of the hair: Determines the craftsmanship, smoothness, and precision of the brush strokes.
     (b) Straightness and toughness of the hair tip and strands: Affects the durability and consistency of the brush.
   - Each brush head is scored on its craftsmanship (up to 40) and durability (up to 60), with a total score of 100 points. The details are as follows,

Sharpness (Jian): Whether the tip of the brush head is sharp and well-defined after trimming.

Evenness (Qi): After the brush is repaired and loosened, whether the bristles form a neat, level surface.

Roundness (Yuan): Whether the entire pen brush head forms a standard cone shape without concavity or convexity.

Health (Jian): Elasticity from brush root to brush head tip, maintaining a stable transition in strength. The root has the greatest elasticity, transitioning smoothly in the middle, and the tip is the softest.

- **Durability/Writing Function** is evaluated on the following criteria, with a total score of 60 points:
  (a) Suitability for writing different scripts.
  (b) Whether the pen brush tip maintains integrity during writing without falling apart.

C.4 Jury Composition and Scoring Process

- **Jury Composition:** The jury consists of six experts, divided into two groups:
- Each group of judges evaluates the same products independently, providing three separate scores for craftsmanship and durability.
- The scoring process is conducted anonymously, with products identified only by codes, and no information about the manufacturer or price is provided to the judges.
- Judges are prohibited from communicating or discussing their evaluations to maintain objectivity and prevent bias.

C.5 Summary

The evaluation of brush pen quality involves a meticulous and detailed process, encompassing structural analysis, classification, grading, and scoring. The criteria ensure a thorough assessment of both the physical attributes and functional performance of the brush pens. The structured approach, combined with anonymous and independent scoring, guarantees a fair and objective evaluation, upholding high standards in brush pen quality assessment.

D Detailed Procedure for Referral Design and Implementation

This section describes the design and implementation of a referral network that strategically assigns business suppliers to clients within a structured framework. By utilizing a systematic algorithm, the referral process ensures that each client receives appropriate recommendations and each supplier is fairly considered. The methodology emphasizes optimizing network strength, business-product relevance, and minimizing undesirable partnerships such as processing firm.

D.1 Screened referral

The initial setup began with the main treatment, where approximately half of the suppliers and clients were designated as treated, as illustrated in Figure 2. This setup facilitated comparisons between treated and untreated firms. Using the 2019 survey data, we divided 295 client firms into two groups: 147 were assigned to the treated group, and 148 to the control group. Similarly, 450 suppliers were randomly divided, with 223 classified as treated suppliers and 227 as control suppliers. Given that our baseline survey, conducted in 2021, also served as the foundation for our baseline analysis, we ensured that these assignments in 2019 were also balanced in 2021, as shown in Table 1.

The referral process was focused on generating screened referrals. For all treated clients, two recommendations for treated suppliers were produced using a predetermined algorithm. Similarly, two recommendations for untreated suppliers were generated for all untreated clients. This process was guided by two specific networks, each designed to enhance the precision and relevance of the referrals.

To implement this concept, we undertook the following steps:

1) **Network categorization.** Initially, we combined the 2018 and 2019 survey data to form a foundational network dataset. For each supplier-client pair, we sought to identify close competitors of an existing partner or existing partners of a close competitor, focusing on similarities in product and price. Specifically, we determined which competitors of each supplier were not currently transacting with the corresponding client, and vice versa for each client with respect to suppliers. These identified relationships were stratified into two distinct networks based on the level of competition:

a) Network 1: This stronger network includes pairs of firms where a close competitor (either a supplier's competitor also acting as a supplier or a client's competitor also acting as a client) shared the same price and product with the focal firm.

b) Network 2: This weaker network consists of pairs of firms where a close competitor shared only the same product with the focal firm, regardless of price. Additionally, we confirmed that Network 1 is a subset of Network 2, ensuring that the strongest links are not omitted in the latter referral algorithm; instead, their weights are adjusted within the algorithm.

2) **Strength variable creation.** These two networks facilitated the generation of candidates for potential partnerships. For each pair identified within these potential partnerships, we developed a 'strength' variable to rank the candidates based on the breadth of their existing connections. This metric was essential for evaluating the suitability of potential partners, with suppliers that had extensive dealings with a client's close competitors considered particularly desirable.

3) **Referral algorithm.** Finally, we created the referrals using an algorithm that ensured that all firms got some referrals about the potential partners and no firms got too many referrals. It turns out it is also possible to assign costs to each linkage mentioned above and find the minimum cost optimal matching. We chose the following costs (i) first link to a supplier is free, every subsequent link is expensive, to ensure that many suppliers are reached; (ii) links are ordered so that strong same price and product in Network 1 > weak same price and product in Network 1 > strong same product in Network 2 > weak same product in Network 2 (Here strong means strength ≥ 2). This ensures that the algorithm tries to use strong network links first. The algorithm guarantees that the flow is maximal, therefore if we link one of these clients to a supplier another client must lose at least one referral (in this case it practically means that every second order neighbor of these suppliers is at capacity as well).

We create **screened** referrals with the following objectives:

(1) Each client has two **screened** referrals to suppliers.

(2) Each existing supplier has at least been referred onece.

(3) We guarantee the final referrals to be spread out among existing suppliers.

This algorithm generates two recommendations for each client firm, referred to as the type A link and type B link, and provides between one and four recommendations for each supplier firm. We summarize the screene referra results as follows,

1) All client and supplier firms were successfully reached.

2) Each of the 295 client firms received two screened referrals (with hypothetical referrals provided for control clients).

3) Among the 450 suppliers, 326 were referred once, 112 were referred twice, 8 were referred three times, and 4 were referred four times.

D.2 Unscreened referrals

The idea of the unscreened referrals was to leverage the firm data, based on the intuition that product similarity contains information about good matches, by referring a partner which produces using the same type of hair (when applicable). That is, for each client we randomly chose an unscreened recommendation of a supplier with the same treatment status, and in the same broad industry as the screened referral – type A link. The unscreened recommendations were generated as follows: If the industry of the screened referral type A was handle or processing firm, we randomly selected a supplier within the same industry. If the industry of the screened referral type A was hair, we examined the main product of the client (e.g., goat hair brush pen) and selected a hair producer whose main product was that specific hair type. For producers of make-up pens, which typically use a mix of materials, no restrictions were placed on the referred brush head producer. We ensured that these unscreened recommendations did not include any existing partners of the client and were distinct from the firm's screened recommendations. We define the unscreened referral as type C link.

D.3 Information treatment

A similar procedure was replicated for the untreated supplier-untreated client pairs by creating hypothetical screened and unscreened referrals. The untreated clients were randomly divided into two groups. One group received the information treatment. For each client in this group, we selected the hypothetical screened referral link B as the information intervention. This referral served as the information-only recommendation for the client firm. These firms are referred to as information-treated firms, though they were not part of the main treatment.

D.4 Subsidy rule

In information referrals, we told the two parties that the researchers and the local government are conducting a research study, and we think that the referred firm would be a good potential business partner. In the screened and unscreened referrals, we also offered a subsidy for the first transaction bwteen client firms and the referred supplier firms, which covered 50% of the transaction value up to a cap of 1,500 RMB per transaction, and which was valid for two months. In both types of referrals, we gave coupons to both firms which included the contact details of the referred partner. In the subsidized referrals only the client firm could ask for the 50% subsidy, and to claim it they were required to submit: (1) a video of the face-to-face transaction, (2) both coupons signed by the supplier and the client, (3) an invoice documenting the transaction, and (4) an itemized list of all goods purchased.

D.5 Implementation challenges and modification of the plan

As the implementation progressed, several challenges emerged that necessitated revisions to the original referral design. 1) First, when we conducted survey in 2021, some suppliers and clients went out of business after the initial recommendations were made. This required the creation of new referrals to replace those lost due to these exits.

2) Additionally, in 2021, some firms switched roles, moving from supplier to client or vice versa. These switchers required new referrals based on their new roles. In these cases, the algorithm adapted by creating referrals using the new business type, relying on Network 2 (same product) since price data for these firms was unavailable.

3) Another significant challenge involved the replacement of processing firm referrals. We found that some initial screened recommendations involved only processing firms (both type A and B referral links) for certain clients, which were later found to be less desirable for clients. The original plan was therefore adjusted to replace these "bad" recommendations with more suitable

alternatives. The decision was made to avoid processing firms entirely when selecting replacement referrals, though it was acknowledged that some clients might still require processing partners.

D.5.1 Adjustments and new objectives

To address these challenges, several adjustments were made to the **screened** referral process. We modify our algorithm and create new **screened** referrals with the following objectives:

(1) Each existing (alive) client has two **screened** referrals to existing suppliers (including the old effective referral and the new referrals).

(2) Each existing supplier has at least been referred once. Some suppliers may now have zero because their referred client went out of business.

(3) When a referral to a client is replaced, the new referral (i.e., new supplier) should be in the same industry as the previous referral (the supplier who exited and is being replaced). If both are replaced, then the replacement of the A-list supplier should be in the industry of the previous A-list supplier and the replacement of the B-list supplier should be in the industry of the previous B-list supplier.

(4) We want the final referrals (old+new, after deleting the ones involving exiting firms) to be spread out among existing suppliers, as before.

(5) We drop all referrals involving firms who switched supplier-client status, and make them new referrals using the usual principles.

(6) We drop all so called "bad" referrals (botg Type A and B referred suppliers are processing firm) and make the affected firms new referrals, which are not processing firms, using the usual principles.

D.5.2 Adjustments of algorithm

We specify our adjusted algorithm as follows,

1. New network categorization. We create a new network of candidate referrals by implementing the following procedures:

(a) Drop all links to/from firms who switched business side. Change the sides of these firms (from supplier to client or from client to supplier, i.e., create new links with source/target etc).

(b) Merge in the new candidate referral links for the switcher firms.

(c) Drop all firms who exited.

(d) Drop all processing suppliers (to make sure they are not used in a referral).

2. Referral classification. We then categorized the referrals made in the field into good and bad screened referrals. Good referrals were those that (a) connected firms that had not exited the market, (b) involved firms that had not switched business roles, and (c) did not involve both type A and B links being assigned to processing referrals. Any referrals that did not meet these criteria were classified as "bad."

3. Adjustment of referral network. We next adjust the candidate referral network and set up capacities for all objectives except objective (3).

(i) Delete good referrals from the new network of candidate referrals.

(ii) For each client firm in the new candidate referral network, assign an initial capacity of 2. Then reduce this by the number of good referrals this client has.

(iii) For each supplier firm in the new candidate referral, set its counter (i.e., how many times it has been asked) to be the number of good referrals it is involved in.

(iv) Delete all type C referrals from the new network of candidate screened referrals since pre-existing type C referrals have already been implemented in the field.

4. Adjust further for objective (3).

We then consider each client firm in the new network who has non-zero capacity because one or both of its referrals exited. (ignore other kinds of bad referrals.)

(i) If that client has capacity 1 and one referral who exited then take the industry of that supplier, we delete all candidate recommendations from the client to suppliers who are not in that industry.

(ii) If the client has capacity 2 (i.e., 2 bad links) and one or two prior referrals who exited, then similarly to what Oliver suggested the client needs to be replaced by two client nodes, and then (i) performed for one or both of them, corresponding to the exiting bad referral.

5. Implementing the algorithm. We finally assign Type A, B and X. For replacement referrals that are replacing exited suppliers, assign the category A/B of the previous referral who exited. For all other referrals being made, assign the category X.

D.5.3 Summary of the results of modification

We present the summary on the latest results and algorithm:

1) We have 44 out of 295 clients who have lost one of their recommendations. These have been replaced by another firm from the same industry, so this shouldn't cause any issues with the A-B-C types.

2) We have 24 clients who had 'bad' screened recommendations (double processing suppliers) and therefore needed 2 new referrals. Currently they all get 2 non-processing screened referrals without any restriction. These 24 clients with 'bad' recommendations will get a new type C as well. So they will end up with six referrals: ABC processing, and ABC non-processing.

3) We have 3 clients that have lost all their supplier assignments. In the current assignment they all get 2-2 new brush head suppliers. All of their type C referrals are from brush as well. Originally 2 of them had brush-brush-brush for A-B-C so the new assignments perfectly follow the previous industries. One of them had brush-handle-brush as A-B-C, now it becomes brush-brush-brush.

4) We have 2 clients that original to be suppliers. Since they don't have a type C recommendation yet, so we only made sure that their assignments are non-processing supplier firms.

5) The current assignment works as follows: Clients in 1) are only linked to suppliers from the proper industry, which assures a correct match. For all other clients we simply removed edges pointing to processing suppliers. Then we maximized flow and minimized costs. The cost minimization here is only responsible for balancing recommendations across suppliers (i.e. we want to reach as many non-processing suppliers as possible, and we actually reach them all) and to prefer strong-narrow edges.

6) As outlined above, we assigned proper referrals to all clients. However, from the supplier side, there are 41 suppliers that we did not reach with new referrals, as they were retained in the old referrals. All of these are processing suppliers, and 39 of them were included in the 'bad' recommendations. As a results, almost all suppliers are reached. Some processing suppliers are

only reached by the old triple-processing recommendations.

For the unscreened referrals, we continued using the original candidate pool but refined it by removing any missing samples.

E Detailed Procedure for Marketing Offer Experiment

To implement the idea of marketing intervention, recall that for each control client in our main intervention we created two screened referrals, some of which were information-only and others unmade referrals. We used this sample of referrals, including the information referrals because they did not lead to subsequent transactions.

E.1 Two new interventions

We design two new interventions in the second phase experiment as follows,

1) Enhanced information (EI): The information was presented in a one-page document that included details about the supplier, such as the type and price of its products, along with the supplier's contact information. The enhanced information treatment involves informing the supplier (or client) that the referred client (or supplier) is aware of them and that both parties are considered a good match. The supplier is then encouraged to take the initiative by providing a free sample to the client. Specifically, the enhanced information is communicated to the firm as follows:

a) The referred firms are aware of your business and understand that researchers believe the two of you would make excellent partners.

b) We have evidence from previous referrals indicating that firms are often more satisfied with their referred partners than they initially expected.

c) For a supplier firm: We encourage you to reach out to the client by sending a free sample along with a price quote. Include information about your main specialty and the number of years you have been in business.

d) For a client firm: We encourage you to reach out to the supplier to request a free sample and a price quote.

2) Marketing offer (MO): same as enhanced information, this marketing offer was a one-page document providing information about the supplier such as the type and price of its product, in combination with a free sample produced by the supplier if one was available. On the client side, the treatment arms are as same as baseline info treatment.

We introduced the treatment as follows. For a random third of client firms, we administered the enhanced information treatment to both of their screened referrals. For the remaining two-thirds of client firms, we administered the enhanced information treatment to exactly one of their screened referrals, and the marketing offer treatment to their other screened referral. This design allows us to evaluate learning effects. Indeed, the valuation friction suggests that once beliefs are recalibrated, the firm should contact other referred partners, while the contacting friction suggests that once the supplier learns the contacting technology, namely the marketing offer, it should use it to contact other referred partners.

E.2 Randomization

In the second phase of experiment, we divided the remaining contorl client firms (132) into two groups: One-third of the client firms (43) were assigned to the untreated group, while the remaining two-thirds (89) were assigned to the treated group. Table A16 presents summary statistics in the 2021 baseline survey about both suppliers and clients. All clients and suppliers, regardless of their treatment status, received enhanced information aimed at encouraging further interaction between the referred parties. The enhanced information was communicated in a structured manner. First, the firms were informed that the referral partners were aware of them and that researchers or government bodies believed they would be a good match. Second, the firms were presented with evidence from prior referrals, highlighting that businesses often found themselves more satisfied with their referred partners than initially expected. Finally, specific instructions were provided: supplier firms were encouraged to reach out to their referred clients by offering a free sample along with a price quote and some background information about their specialties and experience in the industry. Similarly, client firms were encouraged to reach out to their referred suppliers to request a free sample and a price quote.

For the second-phase treated client firms (89 in total), we selected the type A link from the pre-existing screened referrals in the first-phase experiment to be included in the marketing offer intervention. This process resulted in 77 hypothetical screened referral links, which served as the foundation for the marketing offer—the gap being due to changes or attrition in supplier firms between 2019 and 2022. For each of these links, we obtained a free sample from the supplier and distributed it to the corresponding client. Additionally, we designed a nice flyer that highlighted both the details and the image of the supplier's main product.

This setup created three distinct types of referral links. The first type included links where a free sample was provided to the client firms (one-third of the links). The second type consisted of links where no free sample was provided, but the client firm was treated with marketing offer with a free sample in another link (another one-third of the links). The final type involved untreated client firms, making up the remaining one-third of the links.

The intervention was designed to test several hypotheses. First, on the free sample links, we hypothesized that there would be a significant number of subsequent transactions, indicating a direct effect of the free sample treatment. Second, on the no-free-sample but treated client links, we anticipated some subsequent transactions, suggesting a client-side indirect effect. Lastly, on the untreated client links, we expected either subsequent or no subsequent transactions. A key challenge anticipated in this design was the possibility of a supplierr-side indirect effect. Specifically, if a supplier experienced a positive outcome from sending a free sample on one link, they might be motivated to send a free sample on another link.