Firm-to-Firm Referrals*

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June 30, 2024

Preliminary and Incomplete

Abstract

We make randomized firm-to-firm referrals between 700 supplier and client firms in the industry producing the Chinese writing brush. Subisidzed referrals lead to subsequent transactions and the partial crowding out of prior partners; information-only referrals have no effect. The referrals increase revenue, profits, 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 are a key partnering friction. The referrals generate large private and social returns.

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Suppliers and clients are essential for doing business, suggesting that frictions in firm-to-firm markets, which constrain a firm's set of suppliers and clients, may constrain business performance and industrial upgrading. Such frictions are recognized to be important for cross-country trade, (Atkin, Khandelwal and Osman 2017a), but are also potentially important within country. Recent work has exploited natural experiments to show that the introduction of new infrastructure, such as mobile phones or a speed train, reduced information costs about potential partners and improved business performance (Jensen and Miller 2018, Bernard, Moxnes and Saito 2019). But we lack evidence on the effectiveness of non-infrastructure-based interventions which are directly targeted to create firm-to-firm links; on the impacts of such interventions on industry outcomes, including the business network, firm upgrading, and welfare; and on whether information costs are the only or even the main friction limiting partnering.

To explore these issues, we conducted a firm field experiment in China in which we evaluated the impact of firm-to-firm referrals. We created link-level variation in screening and subsidizing referrals to shed light on the frictions that limit partnering, and firm-level variation in providing referrals to trace the implications on business performance. We collected data on the firm network to study impacts on network structure; and data on firm activities, such as product quality and variety, and search for partners, to study impacts on industrial upgrading. Our results suggest that matching frictions are an important growth barrier driven partly by firms underestimating the benefits of search; and that referrals increase partnering, improve product quality and variety, increase beliefs about search and the intensity of search, and generate high returns to consumers.

In Section 1 we present our context and experimental design. We work with firms in the industry producing the Chinese brush pen, a tool that was used for writing in ancient China and remains popular today. Our study setting is the globally leading location of production, which consists two urban areas and several rural areas in a single county. The supply chain of the industry has two main layers: input suppliers, which produce the brush head and the handle, and final good producers, which assemble the intermediate inputs and sell the final good. Although many firms engage in multiple activities, firms can be classified based on their main activity as either an input supplier (supplier) or a final good producer (client). This setting is ideal for our purposes. The

industry is spatially concentrated so that search frictions in other contexts are probably higher; the supply chain is simple with only two layers; and product quality and variety, two key dimensions of upgrading, are measurable by us and by industry experts. Our sample consists of about 700 firms in the industry. We surveyed these firms five times between 2018 and 2023, and in each survey wave we collected information on both business performance and the firm-to-firm transaction network.

In 2021 we introduced our referral intervention. As a first step, we designed two types of candidate referrals—firm pairs we expected to be good matches—which differed in how much data we used to construct them. For *screened* referrals we used the full network data, based on the idea that a firm pair may be a good match if the supplier has close competitors already supplying the client, or the client has close competitors already buying from the supplier. We defined close competitors based on similarity in product type, price, and location. For *unscreened* referrals we only used the firm data, and made sure that the supplier, if it was a brush head producer, produced from the same hair type used by the client, but otherwise paired firms randomly.

We randomized half of the supplier firms, and half of the client firms, into the treatment arm. We then constructed a set of candidate referrals between treated suppliers and treated clients, and another set of candidate referrals between untreated suppliers and untreated clients. This latter set, which we sometimes refer to as "hypothetical referrals" serve as a link-level control group for the actual referrals. For each client firm, we created three referrals, two screened and one unscreened. 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.

We then made all the candidate referrals we created between treated suppliers and treated clients. All of these were *subsidized* referrals in the sense that we both provided information about the partner and a subsidy for the first transaction. To provide information, we gave both firms coupons containing the contact details of the other, and informed both that the researchers, working in collaboration with the local government, find the other firm to be a good potential match. To provide the subsidy, we offered the client firm a 50% discount for a first transaction within a two-month period, up to a cap. In a separate treatment arm, offered for a quarter of the hypothetical screened referrals (between untreated firms) we made an unsubsidized *information-only* referral.

We introduced the information referrals between untreated firms to maximize power, because based on a pilot we expected it to have no effect, which was confirmed in the data.

Firm-level take-up, defined as the treated firm taking up the subsidy for at least one referral, was over 60%. Link-level take-up, defined as taking up the subsidy for a subsidized referral, was about 48 percent, with no meaningful difference between screened and unscreened referrals. Thus, firms valued subsidized referrals.

In Section 2 we present results about the business network. We begin with link creation, measured with subsequent transactions after the subsidy period ended. The screened subsidy increased the probability of subsequent transactions by 45 percentage points, and significantly increased the number and value of transactions, highlighting the importance of search-and-matching frictions. The unscreened subsidy also significantly increased these outcomes, but with point estimates about half as large, suggesting more specifically a search friction in finding the right partner. The information referrals had small and insignificant effects on all measures of transactions, indicating a matching friction that constrains transactions even when the partner has been found. We also have information on firms' satisfaction, because in the follow-up surveys, for each referred link—both actual and hypothetical—we asked firms how satisfied they were, or thought they would be, with the referred partner. We find generally positive and significant treatment effects, implying that firms underestimated the benefit of our referrals, otherwise their expected satisfaction should have been on average correct.

The referrals, by creating new links, could crowd out existing links. To explore this partner-stealing effect, we take the sample of pre-existing links between suppliers and clients, and ask whether treating one of the partners influences the level of activity over the link. We find that treating either or both firms reduces the probability that the link remains by about 20 percentage points, and find negative impacts on the number of transactions and transaction value too. Heterogeneous-effect regressions show that links are more likely to be kept if they involve partners that are larger or considered more satisfactory, suggesting that crowding out may partly reflect a reallocation to more suitable partners.

In Section 3 we present results about firm performance. Among suppliers, we find that the

treatment is associated with significant gains in revenue, profit, hours worked, number of clients, and satisfaction with clients. For example, we estimate revenue gains of 24 log points. These results suggest that the referrals created large gains to supplier firms. Among clients, we find that the treatment is associated with significant gains in the number of suppliers and satisfaction with suppliers, but not other outcomes. To dig deeper, we then remove the sub-industry of make-up pen producers from the sample of clients (20% of clients) and divide the remaining brush pen producers into two similar-sized subgroups based on whether they reported themselves to be growth-oriented at baseline. Among growth-oriented brush pen producers, we find significant and large gains in revenue, profit, operating cost, the number of suppliers, and satisfaction with suppliers. For example, we estimate revenue gains of 43 log points. Among non-growth-oriented brush pen producers, we estimate insignificant gains for all outcomes except for satisfaction with suppliers. These results suggest that while we are underpowered in the full sample of clients, the referrals improved the performance of growth-oriented brush-pen producers.

There are several potential concerns with these results. First, the network-level crowding documented above suggests that the difference between treated and untreated firms may partly reflect partner stealing. We address this issue in two ways. First, we note that partner-stealing predicts a treatment effect for non-growth-oriented clients as well, which we do not observe; and second, we show that exposure to partner-stealing, measured with the share of prior partners receiving the treatment, is not significantly associated with firm performance and does not meaningfully change the treatment effect. Thus, partner stealing does not seem to affect our firm level results, perhaps because firms can 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 their validity. We note that in most subsequent results involving intermediate outcomes we find significant impacts in the full sample of clients; that in these results we impacts are meaningfully larger for growth-oriented brush pen producers; and that when using as an outcome firms' less noisy five-point-scale evaluation of their growth, we find significant revenue and profit effects in the full sample of clients. These findings provide internal validity to our results and support the interpretation that we are underpowered with traditional performance measures. A third concern is

experimenter demand effects. To address it, we establish analogous results for outcomes plausibly less affected by demand effects, such as the owner's phone bill and our enumerators' evaluation of activity in the business.

To explore the mechanisms behind our findings, we look at impacts on intermediate outcomes. We have evidence on two mechanisms. The first concerns product quality and variety. For supplier firms we find a significant increase in product quality—measured by independent experts—in response to the treatment. For client firms we find a significant increase in having a second product, and in the share of revenue coming from a second product. In this industry, second products are generally of higher quality and higher price. Thus, supplier and client firms appear to have made complementary improvements in quality and variety to take advantage of the referrals. The second mechanism concerns beliefs about the value of partners. We find that both suppliers and clients increase their beliefs about the benefit of partners and spend more time searching for partners. We also observe a significant increase in the number of non-referred partners for suppliers and for growth-oriented clients. Thus, firms appear to have increased search in response to treatment.

In Section 4 we study the returns from our intervention and the frictions that prevented firms from earning them. We start by noting that the documented gains come at a cost, which, when comparing the information and the subsidized referral, is the value of the subsidy. 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 could have earned these returns if they financed the subsidy for the information referrals which they instead did not take up. What prevented firms from transacting? In our survey of firms receiving the information referral, two answers were salient: firms did not believe the referred partners were good or did not know how to approach them. The former answer, about misbeliefs, is consistent with our findings that firms underestimated their satisfaction with the referrals and that the treatment increased their valuation and intensity of search.

At this stage, a relevant question is whether there are cheaper ways than the subsidy to overcome these potential frictions and induce take-up. In 2023, we implemented a small-scale trial of one such intervention: we prepared a basic marketing offer, which typically included a free sample, on behalf of the supplier, and took it to the client. This intervention addresses client-side misbeliefs

by providing verifiable information, and supplier-side lack of contacting skills by doing a marketing offer for them. We randomized this intervention among the hypothetical referrals in the control group of our main intervention. We find that the marketing offer significantly increased transactions. Although it was only about 30% as effective as the subsidy, it came at 0.5% of the cost, implying that it was 60 times as effective. This result suggests that the design of matching programs could further amplify the large returns from firm-to-firm market access. We also find that suppliers and clients receiving the marketing offer were more likely to trade with their other (information-only) referrals, and to exchange a free sample in these transactions. These results are consistent with the two frictions discussed above and highlight the importance of learning effects.

Although the private gains from the referrals are large, social gains may be smaller because of business stealing and the cost of constructing the referrals, or larger because of gains to consumers. Although our evidence speaks against partner stealing in the supplier-to-client market, there is still room for business stealing in the client-to-consumer market. To obtain a lower bound for the social gain, we estimate the impact of the treatment on the consumer surplus by assuming a CES demand system and using the methodology in Cai and Szeidl (2024) which is valid in the presence of business stealing in the client-to-consumer market. We find that the annual gains to consumers were about 3.4 times the total cost of collecting the data and making the referrals, indicating large potential benefits from improving firm-to-firm markets.

We build on a growing literature in development and industrial economics studying the impact of market access on industry performance, reviewed in Verhoogen (2023) and JPAL (2024). Some of this work uses natural experiments to evaluate the impacts of information frictions in firm-to-firm search on business performance (Jensen and Miller 2018, Bernard et al. 2019). Other work studies frictions between firms and consumers or traders (Jensen 2007, Bergquist, McIntosh and Startz 2024), frictions in firm-to-firm information sharing (Cai and Szeidl 2018, Asiedu, Lambon-Quayefio, Truffa and Wong 2023), frictions in firm's selling ability to large buyers (Hjort, de Rochambeau, Iyer and Ao 2024), and quality complementarities in firm-to-firm sorting (Demir, Fieler, Xu and Yang 2024).[1] A related line of work studies firms' market access in the context of international trade,

[1] Related work studies the effects of transportation infrastructure on economic activity (Donaldson and Hornbeck 2016, Donaldson 2018, Hornbeck and Rotemberg 2024).

including the effect of access to foreign buyers (Verhoogen 2008, Atkin et al. 2017a, Alfaro-Ureña, Manelici and Vasquez 2022, Goldberg and Reed 2023), the effect of access to foreign suppliers (Amiti and Konings 2007, Halpern, Koren and Szeidl 2015), and the effect of air or face-to-face connections (Campante and Yanagizawa-Drott 2017, Startz 2024). Our contribution to this body of work is to experimentally document the impact of firm-to-firm referrals on firm networks, complementary industrial upgrading, search for partners, and consumer welfare, and the evidence on a belief-based partnering friction.

We also build on work studying barriers to the adoption of best practices by firms (Verhoogen 2023), which seem common in domains including management (Bloom, Eifert, Mahajan, McKenzie and Roberts 2013) and technology (Atkin, Chaudhry, Chaudry, Khandelwal and Verhoogen 2017b). A central question in this literature is why firms fail to learn about and adopt highly profitable practices. The barrier we identify, firms' pessimistic beliefs about the value of partnering, explains this through the logic that such beliefs discourage experimentation and thus can be maintained in a self-confirming equilibrium (Fudenberg and Levine 1993, Schwartzstein 2014). Our results parallel the evidence on workers' pessimistic beliefs about outside options in the labor search context (Jäger, Roth, Roussille and Schoefer 2024) and contribute by demonstrating the importance of this barrier for firm-to-firm search.

1 Context, Data, Design

1.1 Context

Our study area is in the city of Nanchang, the capital of Jiangxi Province in southeastern China, which has a population of approximately 6 million. Nanchang is a major economic hub with a GDP of around RMB 780 billion (USD 108 billion) in 2023. Nanchang contains a county renowned for its production of the Chinese brush pen, esteemed as one of the Chinese traditional stationery in Chinese culture.[2] Production of brush pens in the county began in around 1979, and earned the county the title "Hometown of China's Writing Brush." Local officials believe that the county

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

accounts for more than 75% of the national market for brush pens, attracting tens of thousands of buyers nationwide.[3] The location dedicated to brush pens consists of 2 main urban areas and 9 rural areas, encompassing 72 streets and villages.[4]

The supply chain of the brush pen is organized into three main layers: (1) firms supplying raw materials like nylon and various animal hairs for the brush head and bamboo and wood for the handle; (2) firms producing intermediate inputs, primarily the brush heads and the handles; and (3) firms assembling the final products and selling them to consumers. These layers are connected via firms' 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. 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 and yet others in different varieties of medium-quality heads.

The main quality differentiation across products 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, measured by the "four virtues" of a writing brush: the tip should be sharp (Jian) for precise lines and detailed strokes; 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 by national guidelines about industry standards, specifically in the National Standard GB/T 34854-2017: Chinese Traditional Stationery - Writing Brush (SAMR 2017). Our local experts

[3] Demand for the brush pens is sizable, especially since China's Ministry of Education has repeatedly called for integrating the education of calligraphy in primary and secondary schools (Yuhan 2023). The buyers and consumers of writing brushes include calligraphy lovers, artists, students and educational institutions offering calligraphy and painting courses, tourists purchasing cultural souvenirs, and the high-end gift market where brushes are given as cultural presents during significant events. These groups demand a variety of brushes in different materials, sizes, and craftsmanship.

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

explained to us that these quality components combine into two main dimensions of the brush head: craftsmanship and durability. The former can be evaluated just by looking at the brush head, while the latter can only be evaluated by writing with the brush head.

In this study we focus on two of the three supply chain layers: firms producing the intermediate inputs, which we will refer to as *suppliers*, and firms producing the final good, which we will refer to as *clients*. In both of these layers there are different types of firms. We will distinguish between business type and product type. Supplier firms have three business types: brush head producers; handle producers; and processing firms, which are hired by client firms to conduct production without using their own inputs. Within brush head producers, we further subdivide firms into three product types by the raw material of their main product: goat hair, weasel hair, or mixed hair brush head producers. Client firms have two business types: brush pen producers and make-up pen producers. Within brush pen producers we further subdivide firms into product types by the raw material of their main product: goat hair, weasel hair, or mixed hair brush pen producers. Finally, make-up pen producers manufacture make-up and painting pens, which are related to the brush pen but are distinct products. These firms generally use mixed hair and pay less attention to quality.

In our location, the production of the brush head is largely done by hand, while the production of the handle features some use of machines. The industry largely operates under a family workshop model, with each household independently seeking its own market. This decentralized production provides flexibility, enabling quick adjustments to meet the specific needs of final good consumers. However, a potential cost is that frictions in the partnering process may prevent firms from finding the best business partners, limiting their growth potential.

1.2 Data

We started our research activities with the industry in 2018 summer. We acquired two datasets 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 took the population census to the heads or managers of the 72 administrative units in

our setting (villages and streets) and asked them to identify firms in the administrative census of their unit involved in brush pen-related production. To validate the accuracy of the information we gathered, we identified respected elders in each of the 72 administrative units and asked them to verify our list corresponding to their unit. The end result of this process was a census of firms in the industry, including business type, address, owner name and phone number. There are 983 firms in our firm census, and while it is probably not comprehensive, we think that 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 collected five main surveys with the firms in our firm census. In the summer of 2018 (continued to the spring of 2019), the summer of 2019, and the summer 2021 we conducted baseline surveys; and in the summer of 2022 and 2023 we conducted follow-up surveys. In addition, we conducted a sixth follow up phone survey in 2024.[5] We were able to survey a large share of the firms in our census in each survey wave. For example, in our 2021 baseline, which is the effective baseline for the referrals intervention, we were able to survey 721 firms. Of these, 280 were client firms; 421 were supplier firms, of which 303 produced brush heads, 44 produced handles, and 74 provided processing; and the remaining 20 firms were outside of our two main supply chain layers, with 15 firms selling raw materials and 5 providing inscribing services.

In each survey 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 product introduction. (3) Supply chain. The number of suppliers and clients, the firm's valuation of and search for suppliers and clients, the firm's satisfaction with and trust in suppliers and clients. (4) Business practices, including time allocation to different tasks such as quality control; simple management practices; 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. We pur-

[5] We also conducted a short phone survey in 2020 during Covid, which is not used in this paper.

chased one item of the main product from most 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. As we discussed above, the main determinant of a pen's quality is the quality of the brush head. The experts grouped items by the type of the raw material of the brush head (goat hair, weasel hair, 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 accompanied each of the five main firm surveys with a network survey in which we collected data on firms' regular suppliers and clients. 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 fully 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 we 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 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. In these surveys 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. We conducted our intervention based on the set of suppliers and clients in our 2019 sample. We constructed all referrals using the baseline data collected in 2019 and 2021. We introduced two types of variations in referrals:

1. Unscreened versus screened. These differed in terms of data requirements: we constructed screened referrals using both the firm and network data, while unscreened referrals using only

the firm data. We expected this variation to shed light on search frictions.

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 expect this variation to shed light on matching frictions.

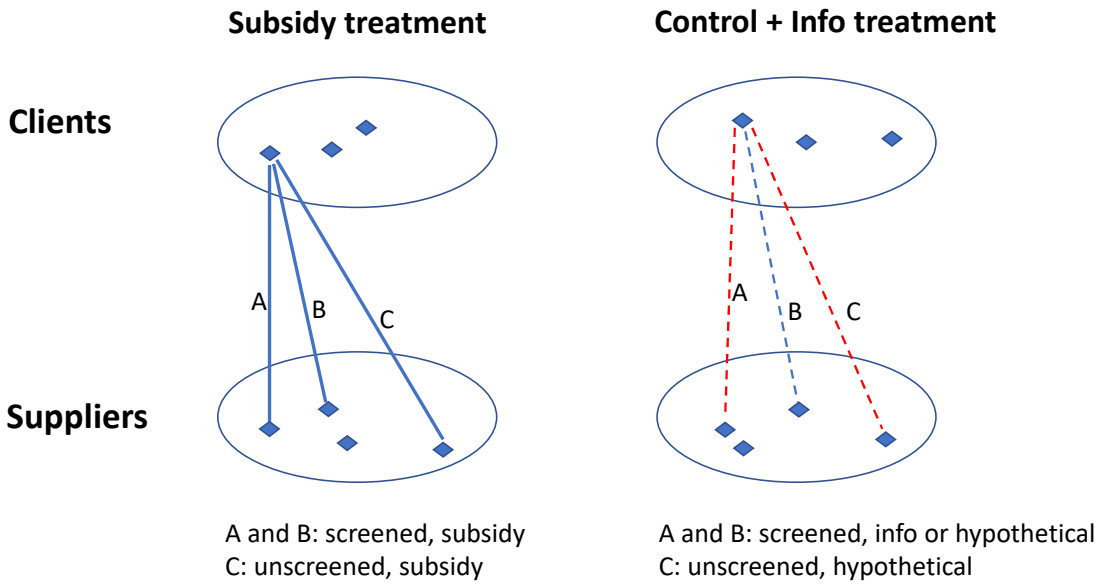
We now turn to explain the construction of the referrals and the way they were implemented. We focus here on explaining the main ideas, and include additional details in Appendix B.

Screened and unscreened referrals. We start by explaining the construction of screened and unscreened referrals. The idea of screened referrals is to leverage the network data, based on the intuition that existing partnerships reflect information about good matches, by referring a partner of a close competitor. To implement this idea, we first created a measure of close competitors, both for suppliers and clients, based on similarity in product, price, and location. 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 matching problem as a problem of finding a minimum-cost flow in a weighted network, and then could apply a standard algorithm.

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 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.

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 think that the referred firm would be a good potential business

Figure 1: Structure of randomization



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, 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.

Structure of treatments. Figure 1 illustrates the allocation of referrals across firms. First we randomized all suppliers, and all clients, into two groups, for which the precise labels are subsidy and unsubsidy, but which, as we explain shortly, can be thought of as treated and untreated. Then we created potential referrals between the suppliers and clients in the subsidy group, and between the suppliers and clients in the unsubsidy group. The first set of referrals can be thought of as a link-level treatment group, and the latter set of referrals as a link-level control group. We sometimes refer to the latter set as "hypohetical referrals". 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 the A and the B referral in the figure, and one unscreened referral, labeled the C referral in the figure. To increase comparability between the screened and unscreened referrals, we ensured that the unscreened referral C had the same business (brush head, handle or processing) as 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, we are able to ensure that all suppliers got at least one screened referral and no supplier got more than four screened referrals. Importantly, we constructed these referrals in the unsubsidy group as well.

We then made the referrals. All referrals we constructed in the subsidy group were offered to the firms as subsidized referrals. Among referrals we constructed in the unsubsidy group (i.e., hypothetical referrals), a random half of the B links were offered to the firms as information referrals. The remaining referrals in the unsubsidy group, including all A links and C links, and the other half of the B links, were not offered. The reason for this implementation of the information referrals was to economize on statistical power. Our expectation, based on a pilot, was that the information referrals would have no effect on subsequent transactions, and this was confirmed in the data. As a result, the firms in the unsubsidy group can be thought of as untreated, and can be used as a basis for comparison the firms in the subsidy (or treatment) group.

To summarize, we have four treatment arms at the link level: screened subsidy, unscreened subsidy, screened information, and control. And we have two treatment arms at the firm level: subsidy and unsubsidy.

Randomization. The randomization of firms into the subsidy and unsubsidy groups was based on stratifying both suppliers and clients according to their main product and baseline sales. We first divided client firms into two groups, brush pen producers and make-up pen producers; and supplier firms into two groups,brush head producers and other input suppliers (handle producers and processing firms). 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 the subsidy arm.

Finally, we note that in 2019 we introduced another intervention in which we encouraged some

firms to join a new e-commerce platform designed for this industry. As part of that intervention, we provided training, including brochures and videos, on how to use the platform, and smart phones to most firms we treated in that intervention. As we show below, the referral treatments are balanced with respect to the e-commerce intervention.

1.4 Summary statistics and balance

Table 1 presents summary statistics in the 2021 baseline survey about both suppliers and clients. From here on, treatment refers to the subsidy firms. Columns 1-3 report summary statistics for suppliers. Column 1 shows the mean value for untreated (unsubsidy) 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. Suppler firms have about 2-3 employees, while client firms have about 6 employees. These values include both formal and informal (e.g., family) employment. Turning to financial performance, the average revenue of supplier firms is about RMB 140,000 (USD 24,500).[6] The profit of supplier firms is about RMB 70,000 (USD 12,000) so that profits account for about 49% 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 as well: their revenue is about RMB 850,000 (USD 132,500) and their profit is about RMB 370,000 (USD 57,800), so that profits account for about 44% of revenue. The large standard errors indicate that the mean values reported in the table mask much heterogeneity across the firms in our sample. Finally, about 70% of suppliers, and about 46% of clients are growth-oriented, as measured based 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.

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

[6] 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: Partnerships						
Num Regular Clients	5.595	6.647	1.052	15.745	14.561	-1.183
(firm data)	(9.706)	(13.583)	(1.170)	(21.447)	(19.461)	(2.464)
Num Regular Suppliers	2.571	2.552	-0.018	6.102	5.619	-0.483
(firm data)	(3.218)	(2.598)	(0.291)	(7.347)	(6.208)	(0.818)
Num Regular Clients/Suppliers	1.444	1.607	0.163	2.292	2.194	-0.098
(network data)	(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)			0.84			0.99
P-val of Joint Significance of Vars in Panels A-C (2023 sample)			1.00			0.95
Observations	205	201	406	137	139	276

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

of managers is about 53 and 49, respectively. Panel C provides summary statistics on business partnerships. The first two rows report measures collected in the firm survey. Suppliers have on

average about 6 regular clients, and clients have on average about 6 regular suppliers. The third row reports the number of partners (clients for supplier firms, and suppliers for client firms) firms reported on in the network survey that are between the set of suppliers and the set of clients in our baseline sample. Suppliers have 1.5 clients while clients have 2.3 suppliers in these data. These values are smaller for three reasons: (1) links between the supplier and client sample that are not reported in the network data; (2) other links not reported in the network data; (3) links in the network data that are not between the supplier and client sample. For example, we observe several supplier-to-supplier and client-to-client links, reflecting the fact that some firms engage in multiple activities. Because we conducted the network survey quite carefully, and because each link in our sample should be covered by two firms, we think that most of the difference is driven by links of type (2) and (3).

Consistent with the randomization, there is no significant difference between the treatment arms 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 at the 2023 endline survey. 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 went out of business before 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, and is balanced in 2022 for both suppliers and clients and in 2023 for clients, however, it shows a significant imbalance of 4 percentage points in 2023 for suppliers.[7] 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 shows essentially identical results as the table shown here.

[7] 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.

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, for which we know whether the referred firms received the subsidy for an initial transaction. We begin with regressions of the form

$$Takeup_i = \mu \cdot Subsidy\ treatment_i + Strata f.e. + \nu_i. \tag{1}$$

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. Recall that all firms in the treatment group received subsidized referrals. We include strata fixed effects and cluster standard errors by firm.

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 analogous to (1) but in the sample of all *referral links*, including the actual and the hypothetical referrals. In this regression we cluster standard errors by supplier and by client and include both supplier strata and client strata fixed effects. 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.

Table 2: Take-up of subsidy

Dep. var.: subsidy used	Clients (1)	Suppliers (2)	Links (3)	Links (4)
Treatment	0.609***	0.631***	0.482***	
	(0.041)	(0.034)	(0.039)	
Screened				0.472***
				(0.038)
Unscreened				0.501***
				(0.047)
Strata FE	Yes	Yes	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 strata and 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.

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

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

Here each observation is a link ij in a follow-up survey wave t. The sample is all referral links, both actual and hypothetical, that is, the candidate links we constructed receiving the subsidized referral, the information referral, and no referral. The outcome variables measure subsequent transactions. The key independent variables are indicators for screened subsidy, unscreened subsidy, and information (all such links are screened). The controls include indicators for the type of the

referral (A, B, or C referral in the language of Section 1), indicators for the firm's business type (brush pen or make-up pen producer for clients, brush head procurer, handle producer or processing firm for suppliers), fixed effects for the strata of both the supplier i and the client j, and year effects. We cluster standard errors by supplier and by client. Because the treatments are randomized, the key coefficients in this regression measure the causal effect of the screened subsidy, the unscreened subsidy, and the (screened) information referral.

Table 3 reports the results for three main outcomes. 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 46 percentage points, while a subsidized unscreened referral increases that probability by 29 percentage points. Both coefficients are highly significant. In contrast, a screened information referral has a small and insignificant effect on subsequent transactions. Column 2 reports impacts on the number of transactions, and column 3 on the total value of transactions in RMB. The results are analogous: screened subsidized referrals have a large effect, unscreened subsidized referrals a smaller effect, and screened information referrals no detectable effect on subsequent transactions.

These results have several implications. First, they imply that search-and-matching frictions are potentially important in this context. Even though the firms have been active in the industry for over 20 years, are in the same county, and have access to a centralized marketplace, our referral intervention managed to create many new partnerships. Second, screened referrals were more likely than unscreened referrals to lead to subsequent transactions, suggesting that there is value in using the rich network data to screen partners, indicating a search friction. Third, screened information referrals had no effect, suggesting that even conditional on finding a potential partner, firms have difficulty initiating a relationship, indicating a matching friction.

We turn to explore whether firms are satisfied with the referrals. In the follow-up surveys, for each referred link—including the actual and hypothetical referrals—we asked both firms to rate on a 10-point scale how satisfied they are, or think they would be, with the referred partner. We standardized firms' responses and report the treatment effects on the standardized satisfaction measures in Table 4. Supplier firms experienced and increase in their expected satisfaction in

Table 3: Link creation

Dep. Var.:	Link	Num Transactions	Value (RMB)
	(1)	(2)	(3)
Screened Subsidy	0.452***	2.701***	7,792.339***
	(0.038)	(0.304)	(1,095.707)
Unscreened Subsidy	0.288***	1.217***	2,977.162***
	(0.033)	(0.180)	(660.142)
Information	-0.028	0.238	1,483.616
	(0.043)	(0.361)	(1,192.851)
Referral type, business type, strata, 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.

response to both screened and unscreened subsidized referrals, while client firms experienced and increase only in response to screened subsidized referrals. The coefficients are measured in units of standard deviation, and indicate that the referrals improved satisfaction by about 0.6 of a standard deviation for suppliers, and over 0.3 of a standard deviation for clients (for screened referrals). These are meaningful improvements. Suppliers did not experience a change, while clients if anything experienced a slight reduction in satisfaction in the case of unscreened referrals. The lack of change is unsurprising because there was no detectable impact on transactions for information referrals, while the negative effect may reflect that firms were disappointed that they did not get a subsidy offered for their referral.

To interpret these results, it is useful to note that an on-average increase in expected satisfaction is inconsistent with Bayesian updating under a correct prior. If absent the treatment firms' beliefs about the value of partners are correctly calibrated, then on average the treatment should not change satisfaction. Thus, the results indicate that firms were on average too pessimistic about the partners we referred to them: in effect, they underestimated partner quality. This underestimation

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	0.337***	0.363***	0.387***	0.608***	0.701***	0.603***
	(0.094)	(0.091)	(0.093)	(0.116)	(0.120)	(0.119)
Unscreened Subsidy	0.009	0.075	0.036	0.508***	0.504***	0.509***
	(0.088)	(0.086)	(0.090)	(0.114)	(0.125)	(0.125)
Information	-0.045	-0.137**	-0.110**	-0.063	-0.018	-0.112
	(0.064)	(0.058)	(0.055)	(0.145)	(0.144)	(0.143)
Referral type, product type, strata, 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.

is a potential reason for the information treatment being ineffective: firms seem to have thought that they would not be satisfied with the referred partners, and thus did not approach them.

The result that there was no impact on the satisfaction of client firms in response to unscreened referrals suggests that these firms were correctly calibrated about a random referral. Thus, for client firms, probably a large part of the value of referrals came from screened referrals.

In Appendix Table A1 we report heterogeneous-effect regressions in which we interact an indicator for a subsidy treatment with different link characteristics. We find that links are more likely to be created in response to the referral when the seller or the buyer are larger in terms of revenue, when the seller reports itself to be growth-oriented (but not when the buyer reports itself to be growth-oriented) and when the seller and the buyer are kin. These results provide some evidence that new relationships were more likely to form when they were better matches, suggesting that the referrals may have contributed to improving the allocation of the firm-to-firm network.

Table 5: Link destruction

Dep. Var.:	Link	Num Transactions	Value (RMB)
	(1)	(2)	(3)
Client Treated * Supplier Treated	-0.218***	-1.890*	-18,415.465**
	(0.052)	(1.038)	(7,974.835)
Client Untreated * Supplier Treated	-0.198***	-0.877	-14,544.815**
	(0.047)	(1.424)	(7,259.763)
Client Treated * Supplier Untreated	-0.199***	-1.973*	-20,933.792***
	(0.058)	(1.066)	(7,054.210)
Business type, strata, 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, a mechanism we label "partner stealing." We explore partner stealing with the following specification

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

We estimate this regression in the follow-up data, for the sample of pre-existing links between suppliers and clients that existed in our 2021 baseline. 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. 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 (brush pen or make-up pen producer for clients, brush head producer, handle producer, or processing firm for supplier) and supplier and client strata fixed effects. 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

21.5 percentage points. The effects are similar irrespective of whether it is the client, the supplier, or both who receives the treatment. Column 2 shows impacts on the number of transactions. All coefficients are negative, though only two of them are significant. Column 3 reports impacts on the value of transactions. Here all three coefficients are significantly negative and have comparable magnitudes. Taken together, these results show that the referrals treatment not only created new links, it also destroyed existing links. These patterns are consistent with the logic of partner stealing.

Table 6: 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	0.019	4.562*	49,164.144*	0.465*	0.919
	(0.102)	(2.343)	(25,066.885)	(0.269)	(1.157)
Exposure * Client satisfactory	0.255**	-1.208	-13,724.691	0.351	2.529**
	(0.106)	(3.199)	(16,368.142)	(0.367)	(1.169)
Observations	646	646	646	646	646
Panel B					
Exposure * Supplier log sales	0.177***	2.489**	1,095.596	0.477***	1.841***
	(0.033)	(1.201)	(8,840.932)	(0.099)	(0.366)
Exposure * Client log sales	0.001	-0.677	-1,658.855	-0.062	-0.080
	(0.029)	(0.794)	(4,518.495)	(0.087)	(0.311)
Observations	1,234	1,234	1,234	1,234	1,234
Panel C					
Exposure * Supplier growth-oriented	-0.202**	-0.624	-509.038	-0.354	-1.963*
	(0.099)	(1.885)	(12,701.098)	(0.283)	(1.059)
Exposure * Client growth-oriented	0.092	3.158*	24,614.965**	0.366	1.339
	(0.084)	(1.750)	(12,156.863)	(0.250)	(0.884)
Observations	1,238	1,238	1,238	1,238	1,238
Panel D					
Subsidy * Kin	0.407***	2.666	-12,459.261	0.881**	3.904***
	(0.112)	(2.719)	(25,818.091)	(0.348)	(1.288)
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. All specifications include the uninteracted exposure and the heterogeneity-defining variable, and business type, strata and year fixed effects. Standard errors clustered by supplier and client. *** p<0.01, ** p<0.05, * p<0.1.

To explore which links are crowded out, 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. Table 6 reports the results. In this table, to increase precision, we include in columns 4 and 5 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, interesting patterns emerge. Panel A shows that among firms with which the partner is more satisfied, crowding out is weaker. Panel B shows that for links involving larger sellers (but not larger buyers) crowding out is weaker. Panel C shows that for clients that report themselves to be growth oriented, crowding out is weaker. All of these patterns are consistent with better relationships being kept and suggestive of improving allocations. Panel C also shows that for suppliers that report themselves growth-oriented crowding out is stronger. One possible explanation is that these firms are smaller and the lower link survival for smaller firms in Panel B drives the result. Panel D shows that crowding out is weaker over kinship links, which could be because these links are efficient or because these links are maintained due to social obligations. Taken together, the results provide some evidence that crowding out was stronger for links that were less good matches, suggesting improvements in the allocation of links.

3 Effects on firms

Our firm-level estimating equation takes the form

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

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 some measure of firm behavior or performance, such as log revenue. The key independent variable is an indicator for the firm's treatment status. 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

Table 7: 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.

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 partner 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 there are no detectable indirect effects on firm performance, supporting the interpretation of β as a treatment effect. We cluster standard errors at the firm level because there is no evidence of indirect effects on firm performance 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 7 reports the impacts on main firm performance measures. Panel A focuses on suppliers. Column 1 shows that treated suppliers, relative to untreated suppliers, experienced a significant increase in revenue of 24 log points. They also experienced a significant increase in profit of about 15,000 RMB, which is about 19 percent of the profit of untreated firms.[8] There is no detectable impact on operating cost, but columns 4 and 5 show a significant increase in log employment and in the total number of hours worked by all people in the firm. Thus, treated suppliers substantially increased their activity. Turning to partners, column 6 shows an increase in the total number of suppliers, and column 7 an increase in the total number of regular clients, both significant. The latter is not surprising given that our intervention referred clients to these firms, but does indicate that the crowding out induced by referrals documented earlier did not fully undo the effect of referrals 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. Taken together, these results show that the referrals intervention improved the performance of supplier firms.

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 taken two steps to select 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 observations. Make-up pen producers are either much larger or much smaller than brush pen

[8] 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.

producers, contributing noise to the estimates, and because they are in a slightly different business, it is conceivable that the referrals had a smaller impact on them. Second, we divided the remaining sample of clients into growth-oriented versus non-growth-oriented based on their response to a survey question in the 2018 baseline. As we discussed in Section 1.4, non-growth-oriented firms generally lacked the capacity 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 8: 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.

Table 8 reports the results. Panel A focuses on growth-oriented client firms. 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 firms are insignificant for all outcomes except for their satisfaction with suppliers. The differences in precision across these two subsamples are not driven by differences in sample sizes: the size of the non-growth-oriented sample is slightly larger.

These results are consistent with the interpretation that treated suppliers generally benefitted from the referrals intervention, while among treated clients there were two distinct business models: growth-oriented firms used the referrals to expand their business, while non-growth oriented firms used the referrals to improve their pool of suppliers.

3.2 Concerns with measurement, identification and interpretation

We turn to discuss several potential concerns with our main results.

Indirect effects. One key concern is that the treatment induced indirect effects on firm performance. The network-level partner stealing results reported in section 2 document negative indirect effects at the link level. However, it is unclear whether these effects are important enough to meaningfully affect firm performance, since firms may be able to use their network of past partners or the centralized market to find replacement partners.

We address the concern about partner stealing in two ways. First, we note that partner stealing predicts a treatment effect for non-growth oriented brush pen producers as well. This is because the partner-stealing logic predicts that all of these firms are losing partners, but the treated among them, because they receive referrals, have more opportunity to replace the partners they lost. As Panel B of Table 8 shows, the treatment is not significantly associated with better performance in this subgroup of firms, providing evidence against partner stealing.

The second way we address partner stealing is by introducing a measure of exposure, defined as the share of the firm's baseline partners (suppliers for a client firm, clients for a supplier firm) which are treated. To account for the fact that firms typically report to have more partners than we observe in our network data, the denominator we use in this measure is the total number of partners reported by the firm.If partner stealing effects are important, then exposure should negatively

predict business performance. Importantly, because the treatment is randomized, exposure has 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 which are never treated, exposure also has a non-random component. To isolate the purely random component in exposure, we follow an approach motivated by Borusyak and Hull (2023) and 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, which we confirm with balance tests (not reported).

Appendix Table A3 reports the results from regressing the main outcomes on the treatment and exposure. We find that the coefficients of the treatment have very similar magnitude and significance as in the main results reported above. Moreover, exposure does not meaningfully predict firm performance for suppliers, and if anything, has a positive effect on profit and employment in client firms. Estimating the same regression in the subsamples of growth-oriented and non-growth-oriented client firms yields similar results: the treatment effects are essentially unchanged in magnitudes and significance, and exposure effects are if anything, positive for employment in growth-oriented brush pen producers. The positive exposure effects may be explained by treated suppliers, due to product upgrading, creating more value to their pre-existing clients, but we lack the power to explore this effect more fully. We conclude that there is no evidence that partner-stealing is an important driver of the treatment effect in our main specification.

A different type of indirect effect may arise because of business stealing in the final goods market. As treated client firms become better, 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.

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 is less clear. 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 plausible 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 essentially most subsequent results on intermediate outcomes we detect significant impacts in the full sample of clients as well, which are however meaningfully stronger in the growth-oriented subsample. Fourth, and most important, we can address this concern using data we collected in the 2024 phone survey, in which we asked firms to rate the performance of their business since 2020 on a five-point scale in several domains, including product variety, total quantity sold, average quality, average price, revenue, and profit. Appendix Table A5 reports the results. We estimate significant positive effects on all of these outcomes in the full sample of client firms. Taken together, these results raise our confidence in the interpretation that there are positive effects for growth-oriented brush pen producers.

Experimenter demand. A third concern is that treated firms, in exchange for the subsidy we offered them, may have over-reported their performance in the surveys. To address this concern, we collected two sets of outcome measures which are less subject to experimenter demand effects. First, in the 2023 endline we collected measures of the owner's phone use, including the value of their phone bill and the number of calls they made. These outcomes, we believe, are less likely to be subject to experimenter demand effects. Second, in the same survey, we also asked our enumerators, who did not know the treatment status of the firm, to measure the firm's operations in a number of ways: count the number of visitors in the firm, the number of calls the owner makes, rate how busy the owner appears on a five-point scale, count the number of employees visibly present in the firm, and assess the overall operations of the firm on a 1-5 scale. In this scale, 1 represents "extremely poor, on the verge of closing down," while 5 represents "highly prosperous, business is thriving." Appendix Table A6 reports the impacts on these outcomes. In the sample of suppliers, we estimate a positive and significant effect for five of these seven outcomes. In the sample of clients, we estimate a positive and significant effect for only one, the log phone bill. However,

Table 9: 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.

Appendix Table A7 shows that in the subsample of growth-oriented pen-brush clients, there is a positive and significant impact on four of the seven outcomes. Thus, the qualitative results we found in our main specifications remain robust for outcomes plausibly less subject to experimenter demand, suggesting that demand effects are unlikely to drive our results.

3.3 Intermediate outcomes and mechanisms

To explore the mechanisms behind these results we look at intermediate outcomes. The first set of outcomes we consider relate to quality, variety, and price. As discussed in Section 1, we measured quality with the evaluation of independent experts. For supplier firms producing the brush head, and for client firms, we purchased a sample from their main product and had the experts evaluate that product on two dimensions: craftsmanship and durability.

Table 9 reports results. Among supplier firms, we document significant improvements in crafts-

manship, durability, as well as total 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, we find some evidence of an improvement in quality, but the main effects seem to concern improvements in variety. Treated firms were more likely to have a second product, had a larger share of their sales coming from the second product, and had a higher average price for their product portfolio. The latter result is driven by client firms' second product being on average more expensive: these firms tend to have a low-price low-quality main product, and a higher-price higher-quality second product. Consistent with client firms expending their sales of a higher-quality second product, they also spent more time on quality control. As we show in Appendix Table A8, the results for client firms are stronger in the subsample of growth-oriented pen brush producers.

Taken together, these results support the narrative that treated clients expanded product variety into a higher-quality second product, while treated suppliers, to provide the inputs for this higher-quality final good, improved product quality. Thus, one mechanism appears to be that the referrals enabled complementary product upgrading by suppliers and clients.

The second set of outcomes we consider relate to the firms' search activities. In the 2023 endline we asked firms their beliefs about the benefit of finding new partners, measured as the percentage point 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 10 reports the results. For suppliers, column 1 and 2 show a significant increase in their 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 about their beliefs about and time allocated to searching 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

Table 10: 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.

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. For clients, we find a significant impact on the beliefs about and time allocated to searching for suppliers, but not for clients, consistent with the fact that these firms were referred suppliers, not clients. There is a significant increase in personal initiative, and there is a positive but insignificant increase in the number of non-referred partners. Appendix Table A9 shows that in the growth-oriented subsample these results are stronger, and the impact on non-referred partners is highly significant.

Taken together, these results are consistent with 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. Thus, a second mechanism appears to be that the referrals improved beliefs about the value of partners.

4 Return to capital and partnering friction

4.1 Private return

An important question is how the profit gains that resulted from the referrals compare with the cost of the intervention. Given the fact that the information referrals resulted in no take-up, while the subsidized referrals did, it is natural to compare the profit gains to firms with the cost of the subsidy. The implied return to the subsidy is a return that the firms could have earned by self-financing the subsidy, and is thus an intuitive measure of the private return.

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 7 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, so that if suppliers were to fully cover the cost of the subsidy, they would have earned a return of about 800 percent per year. 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 8 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, implying a private return of about 1,700 percent per year. Adding up across suppliers and clients, the total profit to treated firms are about 25 times the cost of the subsidy, corresponding to an annual return of 2,500 percent.

To put these numbers in perspective, it is useful to note that existing estimates of the private return to capital in the development context are on the order of 100 percent per year (De Mel, McKenzie and Woodruff 2008, Banerjee and Duflo 2014). The returns we estimate are an order of magnitude larger, suggesting that the reason firms did not take up the information referral is not a realistic cost-benefit calculation.

4.2 Nature of frictions

Given the large returns to partnering, a key question is what friction prevented firms from doing so absent our intervention. At this stage we find it useful to distinguish between three types of partnering frictions.

1. Search frictions, such as search costs or the lack of search technology. These frictions act as a barrier to finding partners. These are the frictions most commonly considered in search settings, e.g., in the context of the labor market.

2. Valuation frictions, such as underestimating the value of potential partners. These are both search frictions and matching frictions: they act as a barrier to both searching for partners and, if found, contacting partners. The relevance of these frictions is only starting to be recognized (Jäger et al. 2024).

3. Contacting frictions, such as the lack of marketing skills. These are matching frictions which act as a barrier to contacting potential partners (Hjort et al. 2024).

We believe that our results provide suggestive evidence on search frictions and contacting frictions, and direct evidence on valuation frictions. Begin with search frictions. Although by searching for partners ourselves, we effectively eliminated the search friction, the result that screened referrals worked better than unscreened referrals does suggest that there are positive returns to search, providing indirect evidence for a search friction.

Consider valuation frictions. An intriguing result of our paper is that the information treatment did not result in take-up. As we have seen in Table 4, this result may be driven by firms underestimating the referred partners, i.e., a valuation friction. But this does not imply that the same valuation friction limits firms' partnering in general: after all, it is possible that firms simply did not take our referrals seriously, but they may still be well-calibrated about the value of search. However, the result in Table 10 that firms increased their beliefs about partnering and search activities suggests that the valuation friction applies more generally than just for our information referrals, and that our intervention, by changing firms' beliefs, attenuated this friction and created more search. This result about valuation frictions is important because such frictions cannot be

corrected by improving access to partners. Even if information about partners if freely available, as long as firms do not believe that partners are valuable, they will not act on this information.

Finally, consider contacting frictions. Here we have one piece of suggestive evidence, namely that the referrals treatment increased personal initiative, which may have enabled treated firms to contact the new partners they searched for.

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). These answers map into our definition of the valuation and the contracting friction.

4.3 Marketing offer intervention

Under the assumption that valuation and contacting frictions are important barriers to partnering even after search costs have been eliminated, an important question is what are interventions that can reduce these frictions at a lower cost than the subsidy. To explore this question, in 2023 we conducted a small-scale follow-up additional intervention. The idea of the intervention was to engineer an introduction in 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. This intervention was expected to overcome the valuation friction for clients by providing verifiable information about product quality via the free sample, and overcome the contacting friction for suppliers by doing the contacting on their behalf and showing them how to do it on their own using a marketing offer.

We evaluated the marketing offer treatment relative to an enhanced information treatment in which we provided more convincing information that the proposed partner would be a good match for the firm, by explaining that similar referrals to other firms led to subsequent trades. We randomized these treatment arms to the set of hypothetical screened referrals (control referrals) we

created as part of our main 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. 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.

To evaluate the effect of this intervention, we estimate

$$y_{ij} = \delta_O \cdot \mathit{Offer}_{ij} + \delta_C \cdot \mathit{Client\ Indirect}_{ij} + \delta_S \cdot \mathit{Supplier\ Indirect}_{ij} + \mathit{Supplier\ referral\ degree\ f.e.} + \mathit{Product\ type\ f.e.} + \mathit{Strata\ f.e.} + \varepsilon_{ij}. \quad (5)$$

This is a link-level regression in which the sample is all screened referrals in the control group of our main intervention. The outcome is a measure of link-level transactions. On the right hand side, the main variables are an indicator for the link receiving a marketing offer, an indicator for the client receiving a marketing offer from its other screened referral, and an indicator for a marketing offer being sent on behalf of the supplier for some other referral the supplier has. The main set of control variables are indicators for the number of screened referrals the supplier has, which are necessary because a supplier who has more screened referrals is more likely to participate in a marketing offer on some screened referral.

Table 11 reports the results. The marketing offer increased the probability of a subsequent transaction by a significant 21 percentage points. It also significantly increased the number of transactions and the transaction value. Indirect effects to the other referred link of the client are positive and large but insignificant. Indirect effects to the other referred links of the supplier are significant and have comparable magnitude to the direct effect. However, when we look separately

Table 11: 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				0.487***	1.331***	2,664.733***
				(0.118)	(0.365)	(732.606)
Client Indirect * Growth-oriented brush pen producer				0.271**	0.374	621.687
				(0.119)	(0.369)	(741.218)
Marketing Offer	0.208***	0.492**	896.297**	0.065	0.097	95.504
	(0.070)	(0.207)	(412.533)	(0.080)	(0.248)	(498.216)
Client Indirect	0.096	0.190	268.205	0.025	0.110	138.933
	(0.065)	(0.192)	(383.502)	(0.076)	(0.234)	(468.821)
Supplier Indirect	0.171*	0.377	722.313	0.184**	0.373	691.779
	(0.088)	(0.262)	(522.133)	(0.079)	(0.244)	(490.056)
Growth-oriented brush pen producer				0.098	0.245	428.233
				(0.092)	(0.285)	(571.798)
Indicators num times supplier referred	Yes	Yes	Yes	Yes	Yes	Yes
Business type and strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	216	216	216	216	216	216

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.

at the effects of this intervention in the subgroup of growth-oriented brush pen producers, the direct effect becomes larger and the client-side indirect effect also becomes significant.

The direct effect of the marketing offer suggests that it may be possible to overcome the matching friction with a low-cost design. To gauge the magnitude of the effect, it is helpful to 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 yearly horizon, whereas here we evaluated impacts over a 4-month horizon. Therefore, we re-estimated Table 3 for a four-month horizon, which we were able to do because in the follow-up surveys we asked firms about transactions at that horizon as well (not reported). Comparing the coefficients of the marketing intervention to that table, we find that the marketing offer was about 51 percent as effective in creating a new transaction, created about 39 percent as many transactions, which 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 comes at an estimated cost of only 0.5 percent of the cost of the subsidy. Thus, after search cost 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 large gains.

The indirect effects of the marketing offer are evidence for learning on both the client side and the supplier side. The learning on the supplier side can reflect both reducing the valuation friction as they improved beliefs, or the reducing the contracting friction as they acquired a marketing technology. The learning on the client side plausibly reflects reducing the valuation friction, since clients did not acquire a new technology.

4.4 Social return

The private return calculations we conducted above do not reflect the social return from the intervention for three main reasons. First, they ignore the gains in consumer surplus accumulating to the final good consumer. After all, the improvements in the revenue of treated clients must reflect consumers' choices to buy more from these firms, implying through the logic of revealed preference that these consumers are better off. Second, they ignore partner stealing and business stealing effects. Although we did not find evidence for partner stealing in the intermediate input market, it is possible that business stealing was present in the final good market. Third, our calculation ignored the cost of collecting the firm and network data used to create the referrals.

We now turn to account for these effects and compute measures of the social return from our intervention. To incorporate the consumer surplus, we build on Cai and Szeidl (2024) and derive a formula for the gain in the consumer surplus under a CESS 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. Specifically, the gain in consumer surplus equals, to a first-order approximation

$$\Delta CS \approx \frac{\beta_C^R}{\sigma - 1} \cdot \sum_{j:T_j=1} R_j. \tag{6}$$

Here β_C^R is the impact of the treatment on log revenue, R_j is the revenue of 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 extent to which a given revenue gain by treated firms reflects a gain in consumer surplus depends on how substitutable the products are: with high substitutability, the same revenue gain measures a smaller gain in consumer surplus. We will use this formula with $\sigma = 5$ which is 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 account for potential business stealing effects, we report separately the estimated gains in consumer surplus, which are valid in the presence of business stealing as well, and the estimated gains in producer surplus, which are correct in the absence of business stealing effects and overestimate the gains to producers in the presence of business stealing effects. Finally, to account for the cost of data collection, we compute returns relative to the total cost of conducting the intervention, including both the subsidy and the data costs.

We find that the implied annual gain in consumer surplus was about 3.39 times the cost of the intervention. The implied annual gain in producer surplus, an estimate valid in the absence of business stealing effects, was for clients 5.91 times the cost of the intervention and for suppliers 4.23 times the cost of the intervention. Thus, depending on the strength of business stealing effects, the implied annual social gains were 3.39-13.52 times the cost of the intervention. We conclude that the intervention generated large welfare gains, highlighting the potential benefits from policies that improve firm-to-firm market access.

Heterogeneity. Another possible factor driving market-level gains may be reallocation to better firms. We have seen in the context of the network-level results that referred links with larger firms are more likely to lead to subsequent transactions, and that existing links with larger firms, or firms that provide a more satisfactory partnership, are less likely to be discontinued. These results are suggestive of improved allocations. To test for improved allocations at the firm level, we estimated heterogeneous-effect versions of our main regressions where we interacted the treatment with measures of firm size, price (a proxy for quality) and partners' average satisfaction (not reported). We did not detect robustly significant patterns, and concluded that either we lack the power to document heterogeneous effects or such effects were not important in our setting.

5 Conclusion

We believe that our results lend support to the following narrative.

1. Firms underestimate benefit of partners and do not search.

2. In response to referrals, firms replace and expand partners.

3. Suppliers upgrade quality and clients expand variety in a complementary fashion.

4. Firms increase their beliefs about and intensity of search.

5. As a result of the previous two mechanisms, firm performance improves.

6. Large private and social gains.

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A Appendix

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

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.

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 $h_j = \tilde{h}_j + \gamma T_j$.

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 E, maximizing (8) subject to $H + P_J Q_J = E$ 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

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

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

The revenue of firm j is

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

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

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

where T_j is orthogonal to ε_j, so that the regression coefficient equals $\beta=\gamma(\sigma-1)$.

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,

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

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

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

B Detailed description of experimental design

C Data and surveys

D Supplemental tables and figures

Table A1: 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	0.083***	0.579***	1,355.250***	0.216***	0.820***
	(0.017)	(0.130)	(509.182)	(0.042)	(0.176)
Subsidy * Client log sales	0.057***	0.455***	1,458.530***	0.147***	0.579***
	(0.016)	(0.136)	(548.371)	(0.041)	(0.170)
Observations	1,586	1,586	1,586	1,586	1,586
Panel B					
Subsidy * Supplier growth-oriented	0.096*	0.664**	1,504.990	0.227**	0.877*
	(0.049)	(0.303)	(973.099)	(0.111)	(0.479)
Subsidy * Client growth-oriented	0.002	0.031	-948.373	0.028	0.037
	(0.056)	(0.449)	(1,775.559)	(0.138)	(0.572)
Observations	1,592	1,592	1,592	1,592	1,592
Panel C					
Subsidy * Kin	0.248**	1.271	4,298.996	0.513**	2.477**
	(0.103)	(0.915)	(3,356.418)	(0.257)	(1.034)
Observations	1,592	1,592	1,592	1,592	1,592

Notes: Each panel in each column is a different regression. Sample is all referrals, actual and hypothetical. IHS stands for inverse hyperbolic sine. All specifications include the uninteracted subsidy and heterogeneity-defining variable, and referral type, business type, strata and year fixed effects. Standard errors clustered by supplier and client. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Link destruction: satisfaction

Dep. Var.:	Client satisfaction			Supplier satisfaction		
	Price	Product	Overall	Price	Demand	Overall
	(1)	(2)	(3)	(4)	(5)	(6)
Client Treated * Supplier Treated	-0.468***	-0.467***	-0.504***	-0.501***	-0.478***	-0.552***
	(0.100)	(0.108)	(0.108)	(0.110)	(0.112)	(0.112)
Client Untreated * Supplier Treated	-0.289***	-0.345***	-0.318***	-0.362***	-0.336***	-0.392***
	(0.082)	(0.090)	(0.093)	(0.095)	(0.099)	(0.101)
Client Treated * Supplier Untreated	-0.471***	-0.484***	-0.525***	-0.429***	-0.425***	-0.430***
	(0.116)	(0.112)	(0.121)	(0.097)	(0.093)	(0.093)
Business type, strata, year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,082	1,083	1,081	1,110	1,110	1,110

Notes: Sample is pre-existing links. Outcome variables standardized. 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.

Table A3: 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 A4: 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 A5: 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 A6: 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 A7: 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 A8: 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 A9: 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.