# Relational Frictions Along the Supply Chain: Evidence from Senegalese Traders*

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**Abstract**

Search and trust frictions have historically hindered the ability of small firms to access foreign input markets. We run a field experiment with 1862 small garment firms in Senegal, in which we provide exogenous variation in search and trust frictions of interacting with suppliers in Turkey. Our search treatment connects firms to new suppliers using social media, and our two trust treatments vary the information about the types and incentives of these suppliers. To measure the impact on foreign market access, we mystery shop at all firms. Treated firms are 25% more likely to have the varieties the shopper requests and the goods supplied are 32% more likely to be high quality, driven by the search treatment. However, the trust treatments matter for longer-term outcomes: trust-treated firms are significantly more likely to develop these connections into relationships that persist beyond the study. These new relationships lead to increases in profit and sales, particularly among wholesalers.

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# 1 Introduction

The substantial growth in smartphone ownership and internet connectivity is fundamentally changing many aspects of how small firms in lower-income countries do business. Not only are firms increasingly selling online—with e-commerce revenue in Africa estimated to have doubled between 2019 and 2024—but they are primarily doing so through social media rather than traditional platforms: in a survey of firms using e-commerce across six African countries, GSMA find that 99% do so using social media and 60% do so *only* using social media (GSMA, 2023).[1] Yet, despite the rapid growth of this phenomenon, often termed "social commerce", we still have limited understanding of the fundamental economic frictions it addresses and the extent to which it effectively solves them. This paper is an attempt to fill that gap.

One area of first-order importance that social commerce has the potential to change is how firms find and develop relationships with suppliers. It could do so by alleviating at least two key frictions. The first are search frictions: firm owners can see high quality photos and videos of the wares of different suppliers without having to leave their store. The second are trust frictions: suppliers are able to develop a reputation and buyers are able to share information and coordinate. Existing evidence shows that these frictions are large (Startz, 2024), so if social commerce does meaningfully lower them then it is likely to have an important impact on firms and consumers.

In this paper, we provide what is — to the best of our knowledge — the first experimental evidence on how and to what extent small firms in lower-income countries can use social media to lower search and trust frictions in their supplier relationships. We designed a field experiment leveraging key features of social media to address various combinations of these frictions in the context of a large international import market. Specifically, we randomly allocated 1862 small firms in the ready-to-wear garment industry in Dakar across treatment arms that connected them to new suppliers in Turkey (the second largest source of ready-to-wear garments in Senegal) and varied the information available about the types and incentives of the suppliers.

**Descriptive Evidence** We first provide descriptive evidence from a survey with these firms on how they use social media to interact with suppliers. 85% have bought directly from WhatsApp groups managed by suppliers in the past 12 months, with the median firm having bought from 3 separate groups, and for 81% of firms at least one supplier is in a different country. When asked why they are in such groups, firms emphasise that the groups help them to see more varieties and to compare prices across suppliers. Other platforms, such as TikTok, Instagram, and Facebook are also popular, each used by around a third of firms.

In contrast, while most firms (88%) have heard of traditional B2B e-commerce platforms, such as Alibaba, they are seldom used. 85% of firms have never purchased from these platforms, and, of those who have, about half have done so only very rarely. When asked why, firms report that they find platforms too complicated and they don't trust the information on the platform. Social media has substantial advantages on both of these fronts: most firm owners

[1] Statista estimate that total B2C e-commerce revenue across Africa was 18 billion USD in 2019, increasing to 34 billion USD in 2024 (Statista, 2023).

already use them regularly, and the social nature means that firms can interact personally with the supplier with little need to trust WhatsApp or Facebook directly.

**Treatments** The experiment comprises three main treatments (see Figure 4 for the full design tree). In the first treatment, which we call Search, we add treated firms to the supplier WhatsApp groups of three different suppliers in Turkey. We do not tell firms anything about the suppliers, except that they were recruited by a local team in Turkey.[2] We chose Turkey as our exporter country because it is the second largest source of ready-to-wear garments in Senegal (after China), and in this context Turkish-made garments are well-known to command a large quality premium (ideal for studying contracting frictions).[3]

We then cross-randomise the second and third treatments among the firms in the Search treatment condition. Both of these aim to alleviate trust frictions in the new supplier relationships. In the second treatment, which we call Hidden Types, we do so in a way consistent with a model where suppliers have hidden types (the typical setup for studying adverse selection). In such models, the main channels to overcome trust frictions are information sharing and learning. We thus add Hidden Types treated firms to a fourth WhatsApp group containing other firms matched with the same suppliers, the purpose of which is for them to share information about whether these suppliers are good or bad. We also give treated firms a recommendation for one of the suppliers, both in this fourth WhatsApp group and over the phone.

In the third treatment, which we call Hidden Actions, we aim to relax trust frictions in the new supplier relationships in a way consistent with a model where suppliers have hidden actions (the typical setup for studying moral hazard). In such models, the main channel to overcome trust frictions is shifting buyers to a group punishment strategy. Thus, we inform firms that we will ask them to rate the study suppliers, and that if we hear bad feedback about a given supplier then we will remove that supplier from the study. Moreover, we inform them that we have made this clear to all of the suppliers, and that they therefore have strong incentives to do a good job.

We thus have a total of five approximately equal sized treatment groups: Pure Control, Search Only, Search + Types, Search + Actions, and Search + Types + Actions. Within the Pure Control group, we also cross-randomise a minor sub-treatment that aims to test whether the main reason that firms do not use B2B e-commerce platforms is that they do not understand them. We thus provide a short training on Alibaba covering how to install the app, search for products, contact suppliers, and make purchases and arrange delivery.

**Foreign Market Access** Our primary outcome is a novel revealed preference measure of access to foreign goods. We do this by conducting a mystery shopping exercise in which surveyors, acting as representative customers, make an order from all firms. The goal is to mea-

[2]While this treatment bundles together the role of connecting them to a supplier and the role of doing so specifically using social media, our view–and our experience from various pilots–is that these are effectively inseparable. If we had simply connected them by, say, giving their phone numbers, the suppliers would almost certainly have simply added the firms to the WhatsApp groups anyway. For firms that do not travel regularly, this is simply how business takes place in this market.

[3]This quality premium is large and salient: in a consumer survey in which we elicited willingness-to-pay for goods, randomising whether we said they made in Turkey or China, we found an average Turkey premium of 34% ($p < 0.01$).

sure foreign market access on both a horizontal dimension (access to wide set of differentiated varieties) and a vertical dimension (access to high quality varieties), so the mystery shopper requests a specific type of good and emphasises that they are looking for high quality.[4] On the horizontal dimension, each good that we request is defined by 5 criteria, such as colour and sleeve style, and our outcome is an indicator for whether the good that the firm provides matches at least 3 criteria. On the vertical dimension, the outcome is an index that aggregates three measures related to quality. For the first two measures, we hire experts to measure the quality, and define both a "high quality" indicator and a score out of 50. For the third measure, we attempt to infer whether the good was made in Turkey, as this is a well-known signal of quality in this setting. We pre-specified these outcomes and the regression specification that we use throughout the paper in our Pre-Analysis Plan (PAP).

We find that treatment has a large and significant effect on foreign market access, on both the horizontal and vertical dimensions. First, we pool the four treated groups together (all of whom received the search treatment). On the horizontal dimension, treated firms are 9.0 percentage points ($p$ < 0.01) more likely to find a suitable good (a 25.3% increase). On the vertical dimension, the index increases by 0.421 standard deviations ($p < 0.01$). Looking at the three vertical measures separately, goods from treated firms are 13.9 percentage points ($p$ < 0.05) more likely to be high quality (a 32.3% increase), no more likely to score higher on the score out of 50, and 14.4 percentage points ($p$ < 0.05) more likely to be Turkish-made (a 30.2% increase). We find no effect on the price, so, since there are both horizontal and vertical gains, we infer that treatment increased consumer surplus.

Second, disaggregating across the four treated groups, we find that the coefficients are broadly similar: the effects for the trust-treated groups are not significantly larger than the effects for search only. This does not necessarily mean that trust frictions do not exist: these are small orders (around 20-40 USD) and may be below the threshold at which trust frictions have bite. Nonetheless, trust frictions cannot be so large as to prevent firms from experimenting with new suppliers. We thus conclude that (1) firms are constrained in their access to Turkish-made goods, (2) alleviating search frictions meaningfully improves this access, (3) social media can play a large role in doing so.

**Supplier Relationships** While the previous results showed that social media can be used to improve foreign market access, whether firms are able to realise this benefit depends on whether these connections develop into real relationships. We measure this using data from a follow-up survey that we conducted after 3 months and data from a large mobile money provider. A large share of small to medium sized transactions take place through this provider, and flows from phone numbers of study firms to phone numbers of study suppliers thus provides transaction-level data for orders.

From the survey data, we find that (pooled) treatment increases the likelihood of having a regular supplier in Turkey by 3.9 percentage points ($p < 0.1$), a 23.3% increase relative to control.

[4]Specifically, they say that they are looking for high quality, and that they therefore would like for the good to be made in Turkey, as their view is that such goods are higher quality. This is a very standard thing to say in this context: customers regularly ask whether goods are "from Turkey" as this is a universally-accepted signal of quality.

The coefficients on Search + Types and Search + Types + Actions are larger, with the latter substantially larger at 6.7 percentage points. We find no effect on the total number of suppliers, suggesting that firms have substituted away from a local wholesaler and towards importing directly. From the mobile money data, we find that all Search-treated firms order similar amounts from study suppliers initially. However, firms in the trust treatments order substantially and significantly more after the mystery shopping exercise finishes: pooling the trust treatments together, they order 286.5% ($p < 0.05$) more than Search Only in this period. This implies that the trust treatments meaningfully increased the share of these connections that developed into relationships. The coefficients on all three trust groups are positive and fairly similar, although they are noisy and this data only represents a subset of overall transactions and likely misses the largest transactions.

**Profit and Sales** Finally, to understand which combinations of alleviating frictions ultimately flow through to producer surplus, we collect standard measures of monthly profit and sales in our follow-up survey. Pooling the treatments together, we find respective average increases of 72.2 USD ($p < 0.05$) and 287.0 USD ($p < 0.05$). These are 38.5% and 47.1% increases relative to control. The coefficient in the Search + Types + Actions group (the group with both trust treatments) is much larger than the others, and is consistently highly significantly different from zero as well as significantly different from the other coefficients. The implied increases are very large, and the magnitudes reduce by around half (but remain significant) when we winsorize at the 1% level. When we look at distributional treatment effects–that limit the role of outliers–we find that these average results come primarily from the upper tail of the profit and sales distributions: a small share of firms, starting at around the 75th percentile for the Search + Types + Actions group, see large and significant increases.[5] We find no such effect in a placebo check where we run the same analysis using baseline profit as the outcome. We thus conclude that firms are able to realise meaningful gains from accessing a new foreign supplier by using social media to overcome the search and trust frictions involved.

When we disaggregate the results by retailer versus wholesaler, we find that the effects on foreign market access and suppliers in Turkey are similar for both types of firms. However, the profit and sales results come almost entirely from wholesalers. Thus, while both types firms show improved foreign market access and develop new supplier relationships, wholesalers show the most immediate benefit, perhaps because this technology substitutes for costly travel or because their larger volumes allow them to capitalise on a new supplier more quickly. We do find large negative coefficients on propensity to travel among treated wholesalers, but the standard errors are too large to draw conclusions with confidence.

**e-Commerce** To test whether the main reason that firms seem to prefer social media to B2B platforms is that they do not know how to use platforms, we also measure the impact of our Alibaba training on Alibaba usage. The training has a first stage: it increases the share of firms that have heard of Alibaba, searched for goods on it, and used it to compare prices to those of their regular supplier. However, it has no effect on the likelihood of making a purchase,

[5] Effects on profit and sales concentrated in the upper tail of the distribution are not uncommon in the literature on small firms in lower- and middle-income countries. See Meager (2022) for a detailed discussion of this issue.

which suggests that it ultimately does not meaningfully alleviate search and trust frictions for these firms. Thus, the fact that firms clearly prefer social media as their main way of doing e-commerce likely reflects something deeper about how social media–in this context–relaxes frictions in a way that formal platforms do not.

**Summary of Findings** Our results show that search and trust frictions in accessing foreign inputs are large and that social media can be used to meaningfully reduce them. Specifically, our mystery shopping results show that connecting firms to foreign suppliers via social media improves their access to foreign goods. While the mystery shopping results are driven by relaxing the search friction, the fact that in the trust-treated groups these connections are more likely to develop into relationships—and profits are more likely to increase—suggests that relaxing trust frictions is also important. These results suggest that the rapidly developing digital landscape in lower and middle income countries has the potential to substantially change how firms find, learn about, and develop relationships with suppliers.

**Contribution** This paper builds on several literatures. First, there is a substantial tradition of theoretical work on the implications of information frictions between buyers and sellers dating back to classic papers such as Stigler (1961) on search, and Shapiro (1983) on trust. However, there have historically been fewer empirical papers testing these theories, particularly in lower-income settings where limited contract enforcement makes these issues even more severe (McMillan and Woodruff, 1999 and Banerjee and Duflo, 2000 are early exceptions). This is largely due to (1) challenges in observing buyer-seller relationships and (2) challenges in obtaining exogenous variation that is relevant to the theory. Recently, a growing literature has been developing that overcomes some of these challenges, primarily on the data side (e.g., Startz (2024), Macchiavello and Morjaria (2021, 2015), Steinwender (2018), Antras and Foley (2015)). In terms of theme and context, the closest paper to ours is Startz (2024), which combines detailed survey data from Nigerian wholesalers with an empirical model to estimate search and hidden actions frictions in international imports, finding that both frictions are large and roughly equally-sized. We bring two main contributions to this literature. First, ours is the first experiment to systematically test theories of search and trust frictions in buyer-seller relationships. This means that we can overcome both main challenges: we observe buyer-seller relationships through our survey and mobile money data, and our variation is both exogenous and specifically designed with theory in mind. Second, both our descriptive evidence and our experimental design highlights the role that social media can play in alleviating these frictions, which has otherwise not been discussed in this literature.

The second main literature we build on is a long literature on how e-commerce can improve consumer and producer surplus by alleviating information frictions.[6] The bulk of this literature focuses on formal e-commerce platforms, typically in higher-income settings (two recent exceptions are Couture, Faber, Gu, and Liu (2021) and Bai, Chen, Liu, Mu, and Xu (2023)),

[6]On platforms, see Dolfen, Einav, Klenow, Klopack, Levin, Levin, and Best (2023), Couture, Faber, Gu, and Liu (2021), Bai, Chen, Liu, Mu, and Xu (2023), Barach, Golden, and Horton (2020), Dinerstein, Einav, Levin, and Sundaresan (2018), Ellison and Ellison (2009). On social media, see Goldfarb and Tucker (2019) for a review. A closely related paper is Alhorr (2024), who provides Facebook pages to female business owners in Jordan and finds positive effects on business outcomes, particularly for women who are less able to leave the house.

and for consumer search rather than firm-to-firm. Our contribution is therefore to bring both descriptive and experimental evidence to show how e-commerce in B2B relationships takes on a different form–namely, through social media rather than formal platforms–in firm-to-firm relationships in lower-income countries, settings where the frictions are likely to be larger.

The third main literature is an older literature in international trade that emphasises how networks have for much of history played a large role in solving information frictions and enforcing contracts. For example, Greif (1993) highlights how 11th century Maghribi traders were able to sustain a multilateral punishment system for overseas agents, and that informal information flows through social networks likely played a key role. The classic article that tests these theories empirically is Rauch (1999), which shows that common language and proximity play a larger role in explaining trade in differentiated goods than homogeneous goods, consistent with shared ties playing a key role the types of goods subject to search and trust frictions. While our study is not about networks *per se*, one of the main channels through which social media may alleviate trust frictions is exactly the mechanism in Greif (1993). Our study thus highlights how social media facilitates a modern manifestation of this older idea.

The rest of the paper is organised as follows. Section 2 describes the setting and presents descriptive evidence on the widespread use of social media to obtain information about suppliers. Section 3 describes the sample and experimental design. Section 4 describes the data and empirical methodology. Section 5 presents the results. Section 6 disaggregates the main results by retailer versus wholesaler. Section 7 concludes.

# 2 Setting

## 2.1 Social Media and e-Commerce in the Supply Chain

In this section, we first describe the main channel that we use for the study and then we present statistics on social media usage and formal e-commerce platform usage.

**Supplier Groups** Many suppliers in our setting operate WhatsApp groups with their clients to advertise their goods, post prices, and highlight new items in stock. We will regularly refer to these as "supplier groups." We show examples in Figure 1. A typical group in our setting has one supplier and 50-100 clients, most of whom are regular or repeat customers. These are not discussion groups: the purpose is for the supplier to regularly post high quality photos and videos of their goods (typically only the supplier is allowed to post). It is of course possible and common for buyers to negotiate with the supplier or to inquire about other goods–they can do so by simply sending a private message. These groups may be usefully thought of as virtual storefronts: clients can see what the supplier is selling, and can talk directly to the supplier about any queries.

These groups play a potentially important role in reducing search frictions and, to some extent, in reducing trust frictions. For search, firms can observe a very large number of goods from all over the world directly on their phone, and can easily negotiate and follow up as needed. Importantly, most firms also use social media extensively to sell to their own customers, and so these groups make it easy for them to forward relevant images to their own clients. For trust, a large group with many clients raises the cost of cheating because cheated buyers can easily message other members to share information. The group also makes it easier for the supplier to build a brand, further improving reputation-based mechanisms.

**Social Media** In Figure 2, we present statistics from our baseline survey with 1862 firms in the ready-to-wear garment industry in Dakar. In Panel (a), we plot the share of firms that reported using different types of social media to obtain information about suppliers, such as learning about new varieties or price information. WhatsApp is ubiquitous: 92% of firms use WhatsApp Status, and 86% use supplier groups. TikTok, Instagram, and Facebook are also popular, each used by about a third of firms. Panel (b) shows the distribution of the number of unique supplier WhatsApp groups that firms belong to. Firms are in many supplier groups, with almost half of firms in 5 or more. This is a large number, meaning that they are observing a lot of information about different suppliers all the time. Importantly, these are not simply groups that they belong to but ignore: the distribution of the number of groups that they have bought inputs from in the past 12 months is almost identical.

To understand the reason such groups are so widely used, in Panel (c) we present the responses to a question asking what the main search-based advantages of supplier groups are. Firms highlight both how it allows them to see more varieties (both a wider set and higher quality) and how it allows them to compare prices across suppliers. Finally, in Panel (d), we show the location of the suppliers running these groups. The majority (81%) of firms are in a group with a supplier in Senegal, while a large minority are in at least one group with a supplier in a foreign country. 21% are in a group with a supplier in Turkey, 12% are in a group with a supplier in China, and 6% are in a group with a supplier in Dubai.[7] In total, 27% are in at least one supplier WhatsApp group where the supplier is based abroad. Note that, since this focuses only on WhatsApp groups, this is a lower bound on the share of firms using social media more generally for international trade.

**e-Commerce Platforms** Traditional B2B e-commerce platforms, such as Alibaba, have also been shown alleviate search and trust frictions (see Goldfarb and Tucker, 2019 for a review). Yet, in this setting, they are seldom used: 85% of firms have never purchased from these platforms, and, of those who have, about half have done so only very rarely. This is not because they have not heard of them, as 88% say that they have heard of these platforms. This reflects a broader trend in which large e-commerce companies have had limited success at penetrating African markets.[8] On the surface, it may therefore seem puzzling why social media should be so heavily used in place of formal B2B platforms. In our follow-up survey, we asked firms why they don't use them. Aside from the 39% firms who give no particular reason, among those who do the two most common answers are that firms find them too complicated to use (40%) and that firms do not trust them (33%).

[7]The share in China is likely a large underestimate of total social media interactions with China, as WhatsApp is blocked by China's firewall (it is useable with a VPN) and so other social media platforms–such as WeChat–are much more common. However, since WhatsApp is the main medium used to connect with suppliers in most countries, our survey focused on WhatsApp.

[8]See, for example, `https://restofworld.org/2023/africa-b2b-ecommerce-shutdowns-layoffs/`.

These explanations have different implications. On the one hand, if the binding constraint is that the platforms are too complicated, then this issue is presumably temporary as further digital expansion and familiarity will likely resolve this naturally. On the other hand, a lack of trust in platforms is more fundamental, and may highlight why social media–in which firms interact more personally with the suppliers–has evolved as the dominant form of e-commerce.

These statistics confirm the anecdotal observations that led us to run this study: that social media usage among small firms is ubiquitous, that it plays a large role in their buying and selling activities, and that a sizable share of firms use it as a means of doing international trade.[9]

## 2.2 Ready-to-Wear Garments in Dakar

Our study focuses on the ready-to-wear garment industry in Dakar. Dakar is the capital city and economic hub of Senegal, representing around one quarter of total population (World Bank, 2024). We chose ready-to-wear garments for two reasons. First, the industry exhibits substantial horizontal and vertical differentiation, making it ideal for our study: horizontal differentiation is useful for studying search frictions, and vertical differentiation is useful for studying trust frictions. Second, it is a large and important sector in its own right: in a consumer survey that we conducted with 400 households in Dakar, ready-to-wear garments represented an average of 6% of total household expenditure.

Within the ready-to-wear garment sector, our study places particular emphasis on goods made in Turkey. We chose Turkish-made goods for two reasons. First, Turkey is the second largest source of ready-to-wear garments in Dakar (after China). Second, Turkish-made goods have a reputation for being higher quality than goods made in China, which is ideal for studying contracting frictions. Importantly, on the latter point, highlighting that a good is "Made in Turkey" is a very common way to signal quality in this setting. To quantify this, in our consumer survey we showed households an image of a product and randomised whether we said the good was made in Turkey or made in China. We then asked for their willingness to pay. We plot the CDF of willingness to pay in Figure 3, Panel (a). The Turkey CDF is shifted uniformly rightward relative to the China CDF, with an average premium of 34% ($p < 0.01$). We did the same thing with 144 firms, shown in Panel (b), and obtained the same result. Moreover, it is very common for customers looking for high quality to explicitly specify that they want goods "Made in Turkey": in our baseline survey, 58% of firms report that either "all" or "a lot" of their customers ask if their goods are made in Turkey, in contrast to 16% for China.

[9] As discussed in Section 3.1 a large share of our sample do not have a physical store. One might therefore think that such firms may be more inclined to use social media to learn about suppliers than the average firm with a store. This is not the case. In Appendix Figure A1, we present the same statistics as in Figure 2 but only for the merchants with a physical store. The results are almost identical.

# 3 Experimental Design

## 3.1 Sample

**Firms in Senegal** The main subjects of the study are 1862 small firms in the ready-to-wear garments industry in Dakar. These firms are typical of small, informal, owner-operated businesses in many large cities in lower- and middle-income countries. 33% have a physical store in a market, while the remaining 67% operate exclusively online, primarily through social media. Firms with a physical store were recruited through a census in selected markets; firms without a physical store were recruited through a combination of advertisements on Facebook and snowball sampling.[10]

91% of firms sell Turkish-made goods, with Turkish-made goods representing 40% of sales for the median firm. 33% of firms sell wholesale, which is an important margin of heterogeneity that we pre-specified in our PAP. 7% of retailers and 15% of wholesalers have travelled at least once in the past 5 years for business, so the majority of these firms purchase inputs through both social media and buying from other firms in Dakar. 18% of retailers and 28% of wholesalers have at least one regular supplier based in Turkey. As we show in Section 2.1, these firms use social media, and WhatsApp in particular, ubiquitously to receive information from suppliers. Firms are therefore familiar with the concept of using supplier WhatsApp group to transact with foreign suppliers, but, since only 21% are in a group with a supplier in Turkey, our experiment is still able to generate meaningful variation.

Firms have pessimistic beliefs at baseline about unknown foreign suppliers. 60% know multiple firms owners who have had bad experiences ordering from a supplier online. To measure firms' priors, we asked them to consider a scenario in which they made an order from 10 unknown foreign suppliers, and to give their opinion on what share of the time the order would arrive and have the quality expected. The median firm's response was that this would happen only 50% of the time.

**Suppliers in Turkey** The study involves connecting the 1862 firms in Senegal with suppliers in Turkey. We worked with 30 suppliers, all of whom were based in Istanbul and were exporters of ready-to-wear garments to West Africa. Suppliers were recruited by census of two quarters in Istanbul, followed by a mystery shopping exercise to identify the most active. Notably, all of these suppliers were of Senegalese nationality. While many Istanbul-based exporters to West Africa are of Turkish nationality, there is a sizeable Senegalese diaspora operating in this industry, reflecting the evidence in Rauch (2001) and Greif (1993) that cultural ties have historically played important roles in alleviating search and contracting frictions in long-distance trade. These shared ties certainly do not reduce trust frictions to zero, but they do likely facilitate reputation-based mechanisms. Importantly for our study, they also solve some basic but important frictions such as language barriers and payment technologies. While we

[10]One might be concerned that the statistics on social media usage in Section 2.1 are mechanically large because a large share of the sample was recruited via social media. In Appendix Figure A1, we show the equivalent of Figure 2 but for firms with a physical store only. The results are identical: both types of firms use social media extensively to obtain information from and about suppliers.

could have worked with a combination of Turkish and Senegalese exporters, we opted to focus on Senegalese exporters as we expected our 1862 firms in Senegal to be highly heterogeneous and we wanted to shut down issues of communication and payment systems in order to focus on the core issues of search and trust. The search and trust frictions studied here are fairly general and thus we do not think that our results are special to the case of within-nationality trade.

### 3.2 Treatment Conditions

In this section, we describe the three main treatments and the two sub-treatments. In short, our Search treatment connects firms in Senegal with three suppliers in Turkey. Among such firms, we then cross-randomise two trust treatments to reduce contracting frictions in these new connections. A full design tree is available in Figure 4. We designed treatments to generate exogenous variation in search and trust frictions in ways that both (a) relate to specific theoretical forces, (b) leverage social media in natural ways. Note that all randomisation is across the 1862 firms in Senegal.

**Search** The purpose of this treatment is to reduce search costs of accessing Turkish-made goods, in particular through directly connecting firms in Senegal with suppliers in Turkey. 80% of firms receive the Search treatment.[11] The treatment consists of adding firms to the supplier WhatsApp groups of 3 different suppliers. The suppliers to match with are selected at random, subject to being a match to the merchant's chosen sector.[12] We do not give firms any information about the suppliers, except to say that they were recruited by a team in Turkey in a similar manner to how the firm itself was recruited. We communicate to the control group that unfortunately we cannot add them to any supplier groups at this time, but that we might do so at the conclusion of the study.

**Hidden Types** The purpose of this treatment is to reduce trust frictions in interacting with these new suppliers, and to do so in a way consistent with a model where suppliers have hidden types.[13] In such models, the primary way to solve trust frictions is to facilitate learning and information sharing about the type of the agent. 50% of firms in the Search treatment are treated with Hidden Types–we only implement this treatment among firms treated with Search. This treatment consists of adding firms to a fourth WhatsApp group. This group contains other firms in the study that were matched with the same suppliers, but does not contain any suppliers. We explain that all members of this fourth group have been matched with the same three suppliers and that the purpose of the group is to share information about them. A member of the study team moderates discussion and encourages firms to share information from time to time.

Since no firms have experience with the supplier at this point, we provide an example to begin

[11] We chose 80% as the two trust treatments are only relevant among firms already treated with search. 80% means that cross-randomising the two trust treatments yields five equally sized groups of 20% each.

[12] In particular, we divided the suppliers into buckets of 3, and then randomly allocate each treated firm to one of the buckets.

[13] Models with hidden types are typically those used to study adverse selection.

this process. In particular, treated firms receive a phone call 2-3 days after recruitment from a recommender. The recommender is part of a team of firms–who are not subjects in the study–that we hired before the study began to order similar products from all of the study suppliers. The recommender describes their experience ordering from one of the suppliers that the merchant was matched with and sends a photo of the item as ordered as well as the item that was delivered.[14] They also explain that they are in the same WhatsApp group to share information, and post a similar message in the group.

Despite the fact that treated firms did not know the recommender personally, they generally took this information seriously for two reasons. First, at the end of the baseline survey, we ask all firms if they would be willing to call a few other firms to discuss their experiences working with the study suppliers. They are therefore not surprised when they receive this call. Second, one of the reasons that social media is so ubiquitously used for commerce is precisely the social nature: even if they don't know the recommender, they can ask questions and assess the preferences and knowledge of the recommender.

All firms not in this treatment condition–both the other 50% of firms treated with Search and all firms not treated with Search–instead receive a "placebo" phone call from a surveyor, asking them for their opinion about supplier WhatsApp groups in general.

**Hidden Actions** The purpose of this treatment is to reduce trust frictions in interacting with these new suppliers, and to do so in a way consistent with a model where suppliers have hidden actions.[15] In such models, the primary way to solve trust frictions is to strengthen the incentives of the agent. 50% of firms in the Search treatment are treated with Hidden Actions, cross-randomised with Hidden Types. Treated firms are told the following at the end of the baseline survey:

> I have one last piece of information to give you. As you know, you have been added to WhatsApp groups of Senegalese suppliers in Turkey.
>
> We work with many suppliers in our study. We want to assure you that they are motivated.
>
> We would like to collect feedback on these suppliers so that we can recommend the best ones in the future. To do this, we will ask merchants to rate your experience with the suppliers we have presented to you on a scale of 1 to 5 on product arrival and quality. These reviews help identify the best suppliers, which is beneficial to them and allows us to continue recommending them to others. They are therefore motivated.
>
> If a supplier gets a bad rating, we will investigate and remove them from the study if they did not do a good job. They will therefore lose access to around 150 merchants if they do not do a good job.

[14] We chose the suppliers to recommend based on these "pre-orders".

[15] Models with hidden actions are typically those used to study moral hazard.

> I will give you a phone number that you can use to give your rating or report a problem.
>
> Lastly, I want to emphasise that the suppliers are aware that they are being rated and that, if they receive bad ratings, they will be removed from the study. We can thus assure you that they are motivated.

After delivering this message, the surveyor gives a business card to the merchant. The business card has a phone number to call, and prominently highlights that this number should be used to rate the suppliers and/or to signal any problems. Untreated firms receive a similar card, but without any mention of ratings or suppliers–instead saying that the phone number is for questions about the study. Both cards can be seen in Appendix Figure A2.[16] All suppliers are told a similar message about how the ratings will work.

Note that the experiment does not randomise the incentives provided to suppliers. Instead, it provides high-powered incentives to all suppliers and randomises whether we tell this fact to firms. We make clear to firms not in this treatment condition that we in no way vouch for or provide guarantees about the suppliers in the study–our only role is to make connections.

**Sub-Treatments** We cross-randomised two additional sub-treatments within the pure control group. The first sub-treatment aims to test whether the binding constraint behind the lack of traditional B2B e-commerce platform usage is that firm owners do not understand how to use them. We thus provide a short training on Alibaba that covers how to install the app, how to search for products, how to contact suppliers, and how to make purchases and arrange delivery. The second sub-treatment is a placebo check for the fact that, in the Hidden Types treatment condition, we have connected firms to each other. To ensure that results are not driven by grouping firms per se, we thus also create similar groups here, where none of the firms have been connected with any suppliers.

### 3.3 Randomisation and Balance Check

Overall, there are five equally likely groups: Pure Control, Search Only, Search + Types, Search + Actions, and Search + Types + Actions. We randomly assigned firms to one of these five groups, stratifying on product group (men's clothing, women's clothing, or shoes & bags), an indicator whether the firm has a physical store, and an indicator for whether the firm had prior direct importing experience. Any misfits, due to integer indivisibility or other issues, were unconditionally randomised across the five cells.

Since this is an RCT, treatment is independent of pre-randomisation covariates by construction, absent errors in the randomisation protocol. To check that the randomisation protocol operated as expected, we report a balance check in Appendix Table A1. The differences in means across treatment groups are all small and insignificant, and a joint test across variables has $p$-value 0.724. We therefore conclude that our estimates capture the causal effect of treatment.

[16] For firms for whom the baseline survey was conducted over the phone, the surveyor sends a high-quality image of the business card to the merchant over WhatsApp.

# 4 Outcomes, Data, and Empirical Methodology

## 4.1 Data and Outcomes

**Consumer Survey** In March 2024, we conducted a 15-20 minute survey with 400 households. This survey is unrelated to the main experiment as the experiment does not involve households, but it allows us to calculate two useful sets of summary statistics. First, we use it to measure the relationship between consumer willingness and various important variables in our analysis. Second, we use it to calculate statistics on household clothing expenditures.

**Baseline Survey** Upon recruitment into the study, between November 2023 and January 2024, we conducted a 30 minute baseline survey. The survey contained questions on their supplier relationships, social media usage, e-commerce usage, and profit and sales. For profit, we use the survey question from De Mel, McKenzie, and Woodruff (2009).

**Foreign Market Access** To test whether reducing search and trust frictions via social media improves firms' access to foreign goods, we need a measure of foreign market access. To construct a revealed preference measure of this, we thus conducted a detailed mystery shopping exercise. The goal was to measure foreign market access on a horizontal dimension (access to more differentiated varieties) and on a vertical dimension (access to higher quality varieties), as well as to measure any effects on price. Around two weeks after recruitment, firms are contacted over WhatsApp by a mystery shopper, played by a trained surveyor. Firms are expecting this contact, as we explain to them at the end of the baseline survey that we will put them in touch with customers who often buy high-quality goods.

The mystery shopper explains that they would like to purchase a certain high quality product from Turkey for an event. Each product is defined by five horizontal criteria that are largely unrelated to quality, such as colour, sleeve style, and presence of a graphic (see Appendix Figure A3 for two examples). The mystery shopper proceeds with the purchase–including asking about price and delivery–if the firm offers a good with at least three criteria. The primary outcome for this horizontal component, pre-specified in our PAP, is an indicator for whether the firm offered a good with at least three criteria.

If the firm offers such a good, the mystery shopper buys the good in a random 80% of cases. Then, once the good arrives in our office, two tailors and an expert shoemaker assess its quality according to a 50-point scorecard.[17] To validate the quality measure, we also gave the surveyors conducting the consumer survey a subset of these goods to present and elicit willingness to pay (WTP). We show a binscatter of the relationship between the quality score and WTP in Panel (a) of Figure 5. There is a clear positive relationship, although it becomes flat in the left tail, reflecting the fact that beyond a certain point consumers simply view goods as "low quality". In Panel (b), we classify goods as "high quality" or "low quality" (defined as whether a good

[17] We designed this scorecard together with the these hired experts specifically for this study. Vitali (2024), who studies the relationship between consumer search costs and firm location choices in Kampala, takes a similar approach to measure the quality of garments. Although the details of the scorecards are quite different (hers is focused more on the tailoring skill evidenced in bespoke-made dresses, while ours needs to be more general purpose), we benefited greatly from showing her scorecard to our hired experts as an example of what we were looking for.

is above the median quality score of its product type), and plot the CDF of consumer WTP separately for these two sets of goods. The high quality CDF is shifted rightwards of the low quality CDF, with an average premium of 35%.

The outcomes are exactly these two measures: the high quality indicator and the raw 50-point quality score. The rationale for the binary outcome is that it is not vulnerable to a long left tail of quality scores that, as we saw in Figure 5, are not meaningful in terms of WTP.

Finally, we also attempt to infer whether the good was manufactured in Turkey. As we showed in Figure 3, there is a large premium for Turkish-made goods since it is a strong signal of quality. Thus, while the other two vertical outcomes measure quality directly, in practice quality is not fully observable to consumers and so product origin plays an important role in consumer WTP.[18] For most goods, we record this information from the label, and the outcome is 1 if the label says "Made in Turkey" and 0 if it says it was made elsewhere.[19]

**Followup Survey** We conducted a 30 minute followup survey with similar questions to the baseline survey between February and April 2024, around 3 months after a merchant is recruited to the study. We successfully surveyed 1671 merchants, or 90% of the sample. The followup rate is very similar and not significantly different across the four treated groups, but is 5 percentage points higher and statistically significantly different in the pure control group. The main outcomes are various questions about the number and location of the firms' suppliers, profit and sales, and e-commerce use.

**Mobile Money** We analyse transactions between firms in the study and study suppliers, we use transaction-level data from the largest mobile money provider in Senegal. This contains the universe of transactions between the phone numbers of firms in the study and the phone numbers of study suppliers. This has several advantages over survey-based measures: (1) it is dynamic, so we can see transaction profiles over time, (2) it continues long after the followup survey, (3) it is "real" and not self-reported.

While we do not know the share of transactions taking place through this medium, we expect that it is relatively large, at least for retailers, for a few reasons. First, we asked the non-study firms that we hired to mystery order from all suppliers prior to the study (mentioned in Section 3.2) to record how the supplier asked them to pay, and in 100% of cases they were asked to pay with this particular mobile money provider. Second, in the baseline survey, 86% of firms reported that they often use this provider to pay suppliers when making payments at distance. We thus expect that we see most small-to-medium sized orders, but likely miss larger orders as–anecdotally–these are more likely to take place with more formal methods such as bank transfers or international transfer services (such as Western Union and Moneygram). Since wholesalers tend to make larger orders and have significantly more experience with formal

[18]We pre-specified this outcome, but did not attach it to either the horizontal or vertical dimensions. Since the consumer preference for Turkish-made goods primarily reflects a preference for quality, it seems most fitting to include it under the vertical dimension.

[19]For the small share of goods for which the label does not indicate the origin, we ask the hired experts to (independently) give their opinions as to whether the good was made in Turkey (based on sewing patterns, product style, and any other characteristics), and set the outcome to 1 if they both opine that it was made in Turkey and 0 otherwise. We report robustness to various alternative definitions in the appendix.

methods, we thus expect that this dataset is much more representative of retailers than wholesalers.

## 4.2 Empirical Methodology

Our primary empirical method, described in our Pre-Analysis Plan (PAP), is to estimate the following OLS specification

$$y_i = \alpha + \sum_{j=1}^{4} \beta_j T_{ji} + \delta y_{0i} + \gamma_s + \rho' X_i + \varepsilon_i, \tag{1}$$

where $y_i$ is the outcome for merchant $i$ and $T_{ji}$ for $j = \{1, 2, 3, 4\}$ are indicators for treatment arms Search Only, Search + Types, Search + Actions, and Search + Types + Actions, respectively. $y_{0i}$ is the outcome measured at baseline, if available. $\gamma_s$ are stratum fixed effects. $X_i$ are firm-level covariates, selected by Double Lasso with cross-validation, following the method of Belloni, Chernozhukov, and Hansen (2014).[20] We also report a version of the same regression where we pool the four treated groups into one indicator.

**Inference** Our primary method of inference is randomisation inference, as recommended by Athey and Imbens (2017) and Young (2019). In particular, we compute two-sided $p$-values using 5,000 draws of the $t$-statistic.[21] We report conventional formula-based heteroskedasticity-robust standard errors in parentheses to provide a measure of the variability, but we do not use these for inference directly. As each regression involves four main coefficients, we also calculate and report Romano-Wolf (RW) multiple-testing adjusted $p$-values in square brackets (Romano and Wolf, 2005).

**Indexes** To account for multiple hypothesis testing across outcomes, for any table that presents more than one outcome corresponding to the same broad outcome construct, we also report the results on an index that aggregates the outcomes using the standardised inverse-variance weighted method of Anderson (2008). To be consistent with the fact that the disaggregated regressions may include different covariates $y_{0i}$ and $X_i$, before constructing the index we first residualise each outcome using the covariates that were included in their respective regressions.

**Quantile Regression** As some of our outcomes, most notably profit and sales, may have thick tails and/or exhibit non-uniform distributional treatment effects (see, e.g., Meager, 2022), we also included in our PAP that we may use quantile regression to examine distributional treatment effects where relevant. For these, we follow the same specification as described above,

[20] This means that, prior to each regression, we run lasso to predict $y_i$ and each $T_i$ and include the union of selected covariates. In practice, since this is a randomised experiment, the $T_i$ step selects very few covariates.

[21] Specifically, we use the randomised randomisation-$t$ test statistic described in Young (2019). This amounts to comparing the square of the $t$-statistic, and in case of ties using draws from $U[0, 1]$ . Young (2024) and Ritzwoller, Romano, and Shaikh (2024) note that studentised test statistics have better properties outside of the regime of sharp nulls under design-based inference and are thus more general.

except that we omit the stratum fixed effects, $\gamma_s$, and the vector of covariates, $X_i$, as quantile regressions are much more demanding and the covariate selection procedure in Belloni, Chernozhukov, and Hansen (2014) is designed for linear treatment effect models.

# 5 Results

In Section 5.1, we present results on foreign market access, as measured by our mystery shopping activity. In Section 5.2, we present results on supplier relationships. In Section 5.3, we present results on profit and sales.

## 5.1 Foreign Market Access

In Table 1, we report the main mystery shopping outcomes. In Panel A, we report the equally-weighted linear combination of the four treatment arms. In Panel B, we report the four treatment arms separately, with the number of significant coefficients after adjusting for multiple hypothesis testing (using the Romano-Wolf adjustment) reported underneath the table. In Panel C, we report the two equally-weighted linear combinations of the Trust treatments.

**Horizontal** In Column 1 of Table 1, we report the main horizontal outcome. We find large and statistically significant effects on the horizontal outcomes. The outcome in Column 1 is an indicator for whether the firm offered a product with at least three horizontal criteria.[22] Pooling the treatments together, treated firms are 9.0 percentage points more likely to find a suitable good, significant at the 1% level. This is a 25.3% increase from the control mean of 35.7%. In Panel B, we see that the effect is broadly similar in all four treatment groups, in line with the fact that this is primarily a test of the search friction. This is confirmed by Panel C, which shows that the trust treatments had little impact on this outcome over and above connecting firms to a foreign supplier.[23] The results thus show that relaxing the Search friction by connecting firms with foreign suppliers via WhatsApp groups led to a sizeable increase in the set of varieties that they can provide to customers.

**Vertical** In Columns 2-5 of Table 1, we report the vertical outcomes. The outcome in Column 2 is an indicator for whether the product is "High Quality", defined as whether the product's quality score is greater than its product-group median. Pooling the treatments together, treated firms are 13.9 percentage points more likely to be high quality, significant at the 10% level. This is a 32.3% increase from the control mean of 43.1%. In Panels B and C, we see that the coefficient is positive and similar in all four treatment groups.

The outcome in Column 3 is the raw quality score out of 50. Here, the effect is both small and insignificant. The coefficients are negative in both groups with the Actions treatment, and the

[22]Our PAP specified this indicator variable as the main outcome. Nonetheless, as a robustness check, we use the raw number of criteria as an outcome in Columns 3 and 4 of Appendix Table A2. The pattern of the results is the same.

[23]In our PAP, we noted that we would also report the same outcome separated into extensive margin (agreeing to sell a Turkish-made product at all) versus intensive margin (how suitable was the product provided). We do this in Appendix Table A2. We see that, while the extensive margin effect is positive, the effect comes mostly through the intensive margin.

linear combination in Panel C strongly rejects the null of no additional effect of Actions. As we noted in Section 4, this outcome is vulnerable to a long left tail having an outsize influence that is not particularly meaningful. This is indeed what happens: in Appendix Figure A4 we plot the CDF of quality score by treatment status, and we see a handful of very low quality goods in the treatment group.

The outcome in Column 4 is an indicator for whether the product was made in Turkey. Pooling the treatments together, treated firms are 14.4 percentage points more likely to supply a good saying "Made in Turkey", significant at the 5% level, a 30.2% increase from the control mean of 47.7%.[24] In Panel B, we see that the effect is positive for all four treatment groups.

Finally, to account for multiple hypothesis testing, we aggregate these three outcomes into a vertical index using the standardised inverse-variance weighting method recommended in Anderson (2008). The pooled coefficient is 0.421 standard deviations, significant at the 5% level, and is similar across the four separate treatments. The results thus show that relaxing the Search friction by connecting firms with foreign suppliers via WhatsApp groups led to a sizeable increase in their access to higher quality goods.

**Price** In Column 6 of Table 1, the outcome is the unit price charged by the firm.[25] We find no effect on price: the coefficients are small and insignificant across all the rows.

**Summary** Putting together these results, we find that the treatments led to large and significant increases in firms' access to foreign goods. In particular, treated firms are able to sell a wider set of varieties and higher quality varieties. The fact that we find no effect on the price, while there are gains from variety and quality, suggests that consumer surplus has increased.

Across all of these outcomes, the pattern is fairly consistent: the results are largely driven by relaxing the Search friction. We therefore conclude that finding a supplier of Turkish-made goods is costly, and that WhatsApp can play an important role in alleviating this friction. This does not mean that the trust frictions do not exist: these are small orders, and so for many firms the risk is sufficiently low that relaxing the trust frictions is unlikely to have a large effect. Nonetheless, we can at least conclude that trust frictions cannot be so large as to prevent firms from experimenting with new suppliers.

## 5.2 Supplier Relationships

The mystery shopping exercise shows that there are gains to relaxing the search friction for foreign goods through social media. However, to realise these gains in practice, firms need to overcome the trust frictions (if any) and develop these connections into relationships. Thus, this section examines the extent to which the interventions caused new relationships to develop.

[24] As a robustness check, we report various alternative outcome definitions in Appendix Table A3, including specifications where we only use the information on the label and where we only use the expert tailors' judgements. The pattern of results is the same.

[25] This outcome is only available conditional on finding a suitable good, as the price negotiation step in the mystery shopping protocol came after discussion about the good itself.

### 5.2.1 Survey Data

In our follow-up survey, conducted after 3 months, we asked firms how many regular suppliers they had, and where those regular suppliers were based.[26] We analyse these outcomes in Table 2. In Columns 1, the outcome is an indicator for whether the firm has a regular in Turkey. In Column 2, the outcome is the number of regular suppliers in Turkey. In both cases, pooling all treatments together–including Search Only–shows that treatment caused firms to develop new relationships with suppliers in Turkey. The pooled coefficients are 3.9 percentage points (an increase of 23.3%), significant at 10% and 0.084 suppliers (an increase of 38.0%), significant at 5%.

Disaggregating by treatment arm, for both outcomes the coefficient for Search + Types + Actions (the group where we relax both trust frictions) is substantially larger, around twice the pooled coefficient. This suggests that relaxing trust frictions, and in particular relaxing them together, increased the likelihood that these new connections developed into regular relationships. We also see that the Search Only coefficient is sizeable in magnitude for both outcomes, although it is only significant for the number of suppliers outcome. This provides some suggestive evidence that, for some firms, simply connecting them was enough.

Having seen evidence that new supplier relationships developed, it is therefore natural to ask whether these new relationships complement or substitute for existing relationships. We provide some evidence to address this in columns 4, 5, and 6. In column 4, the outcome is the total number of suppliers; in column 5, the outcome is the number of suppliers in Senegal. The general direction looks closer to a world of substitutes: the coefficients on the total number of suppliers are close to zero, and the coefficients on the number of suppliers in Senegal are of similar magnitude (but opposite sign) to the coefficients on the number of suppliers in Turkey. Finally, column 6 shows an indicator for whether the firm said that they have ended a relationship with a regular supplier in the past 3 months. The coefficients are generally negative, which is also suggestive of substitutes.

### 5.2.2 Mobile Money Data

As discussed in Section 4, we use data made available for this research from a large mobile money provider in Senegal to directly observe transactions between firms in the study and study suppliers. Before turning to formal regression results, we first show broad patterns. In Figure 6, we plot cumulative order value from study suppliers by treatment group over the course of the study.[27] The dashed line shows when we finished our mystery shopping activities. The figure shows two striking patterns. First, over the mystery shopping period, the total value ordered is very similar across the four treatment groups. This suggests that trust treatments were not necessary to make small experiments with the study suppliers when there is no demand risk as a customer is already present. The total value ordered is much larger than the total value purchased by our mystery shoppers, so this not simply coming from buying and

[26]The definition of a regular supplier that we used was that the firm had made at least two orders from this supplier, and intended to continue this relationship.

[27]The pure control group is omitted from the figure because they were not connected to the study suppliers. Reassuringly, we find a negligible number of orders from such firms.

re-selling to us, although we do expect that the mystery shopping lowered the cost for many firms to experiment. Second, almost immediately after the mystery shopping ends, the Search Only line becomes flat, suggesting that these relationships were not lasting. In contrast, in all three of the trust treatments, the total value ordered continues to increase well beyond when the mystery shopping ended, suggestive of continuing relationships.

We formally test these patterns in Table 3. In this table, the omitted category is Search Only, as this outcome is not defined for pure control. Column 1 shows the effect of the trust treatments on the probability of making any order from the study suppliers. We find no significant effect, either in the pooled coefficient or the disaggregated coefficients. In Columns 2 and 3, we test the observation from Figure 6 that only the trust treatments appear to continue ordering after the mystery shopping ends. The outcome in both cases is the total value ordered after the mystery shopping ends, aggregated over weeks to the firm level. Note that we did not pre-specify this outcome, but rather included it after observing the pattern in Figure 6. The coefficient pooling all three trust treatments together in the Poisson regression implies an $e^{1.343} - 1 \approx 283.1\%$ increase, significant at the 5% level. The pooled coefficient in the OLS regression is similar and also significant at the 5% level. When we disaggregate the treatments, we find that the coefficient is positive in all three trust treatment groups. While it is larger in the Actions groups, the difference is not significant. Finally, in columns 5 and 4, we report the effects on total value ordered over the entire course of the study. The coefficients are all positive, although they are not significant.

The OLS coefficients in Table 3 are very similar between total value after the mystery shopping and total value, which is in line with the first observation from Figure 6 that the differences only open up after the mystery shopping ends. Moreover, the fact that the trust treated groups order more after the mystery shopping ends (and thus more overall), but there is no effect on the probability of ever making an order, highlights that these are lasting relationships rather than new firms that start to order after the mystery shopping ends.

#### 5.2.3 Supplier Relationships: Summary

Putting together the results from Sections 5.2.1 and 5.2.2, we find that trust treatments increased the probability that these new connections developed into relationships. From the survey data, these effects come primarily from the Search + Types + Actions group, and, to some extent, the Search + Types group. In the mobile money data, these effects come from all three groups.

### 5.3 Profit and Sales

#### 5.3.1 Mean Results

In Table 4, we report the results on profit and sales in the past 30 days.

Columns 1-2 show the results on raw profit and sales. We find large and statistically significant effects. For profit, the pooled coefficient is 72.2 USD, significant at the 5% level, or a 38.5% increase from the control mean. For sales, the pooled coefficient is 287.0 USD, significant at the 5% level, or a 47.1% increase from the control mean. When we look at the effects of the four treatments separately in Panel B, we see a similar pattern for both outcomes. While the effect is positive in all four groups, it is substantially larger and highly significant in Search + Types + Actions group (including after adjusting for multiple hypothesis testing), which is also reflected in the linear combinations in Panel C. The same pattern holds when we combine these two outcomes into an index.

To limit the influence of outliers, in Columns 4-5 we report the results when we winsorize the outcomes at the top 1%. The coefficients decrease in magnitude by around half on average, but the same pattern remains: the Search + Types + Actions group has a very large and highly significant coefficient, including after adjusting for multiple hypothesis testing.

#### 5.3.2 Distributional Results

It is well-known in the literature studying small firms in lower-income countries that profit and sales tend to be thick-tailed, and that these tails can have outsize effects on the coefficients in OLS regressions. Thus, as discussed in Section 4.2 and specified in our PAP, we use quantile regression to examine distributional effects.

**Quantile Treatment Effects** In Figure 7 Panel (a), we show the quantile treatment effects for profit for percentiles 5-95. Across all four groups, the coefficients are small and generally insignificant for percentiles 5-65. However, starting from around the 75th percentile, the Search + Types + Actions group coefficient becomes large and significant. The coefficients for Search Only and Search + Types are also large at the 95th percentile, but are very noisy. We report the same analysis for sales in Panel (b). The results are similar: there is little evidence of an effect for percentiles 5-65, but it begins to increase at around the 75th percentile for the Search + Types + Actions group, with some positive but noisy effects for Search Only at the 95th percentile.

The increasing trend in both profit and sales from percentiles 75 to 95 also suggests there may be potentially very large effects in the top 10 percentiles. We thus report the same approach for percentiles 90-99 in Appendix Figure A6. These are very demanding specifications using increasingly small subsets of the data, so we would caution against putting great weight on individual magnitudes, and instead we focus on the broad pattern. The coefficients are generally large and positive, further suggestive of treatment effects at the top of the distribution.

**Threshold Regression** An alternative way to analyse distributional treatment effects is to construct a series of indicator variables that are 1 if the outcome is greater than $t$, for a range of $t$, and run OLS regressions where these indicators are the outcome variable (using the specification in Section 4.2). This has the advantage of being unaffected by high variance or measurement error of tail outcomes: all that matters is whether the outcome is above the threshold $t$. The coefficient is interpretable as the treatment effect on the share of firms having an outcome greater than $t$. We report the results in Appendix Figure A5. We find similar results to the quantile regressions: large and positive treatment effects near the top of the distribution for the Search + Types + Actions group for both profit and sales, and some suggestive evidence of positive effects for the other groups at the very top.

### 5.3.3 Profit and Sales: Summary

In Table 4, we saw large average effects on profit and sales. The distributional results in Figure 7 show that these average effects come primarily from large effects for a subset of firms. We do not think that these effects are simply the result of a few outliers that happen to be in the treatment group, for at least five reasons. First, the positive distributional effects are coming from at least the top 5% of the distribution, which is considerably more than a few outliers. Second, the threshold regressions use indicators as their outcomes and thus are immune to the risk of a few observations having outsize influence. Third, the $p$-values in Table 4 highlight that the patterns we observe are very unlikely under the null, including after adjusting for multiple hypothesis testing. Fourth, the results in Table 4 are robust to winsorising the top 1% of firms. Fifth, as a placebo check, we compute the same quantile figures using baseline profit as the outcome in Appendix Figure A7 (we do not have a measure of sales at baseline), and find no evidence of this pattern.

A positive effect driven by the upper tail of the profit distribution is not unusual in the literature studying firms in lower- and middle-income countries. For example, Meager (2022) aggregates the results of six RCTs on microcredit, and finds consistent evidence of little-to-no effects on profit throughout most of the distribution, with large but uncertain effects near the top. Another example is De Mel, McKenzie, and Woodruff (2013), who study the effect of formalisation among small firms in Sri Lanka, and find profit results driven by the upper tail. Moreover, an effect concentrated among a relatively small number of firms is consistent with a small subset of firms developing meaningful relationships with the study suppliers.

## 5.4 e-Commerce Platforms

Our final set of outcomes relate to the Alibaba training sub-treatment. The goal of this treatment was to test whether the binding constraint explaining the very limited use of formal e-commerce platforms is that firms find these platforms too complex. Thus, we regress outcomes relating to Alibaba use against an indicator for whether the firm was in the Alibaba training group. Since we only randomised this training among firms that received none of the main treatments (i.e., the pure control group), we exclude firms that received any of the main treatments from this regression for ease of interpretation.[28]

We report the results in Table 5. The training has a first-stage: treated firms are 6.5pp more likely to have heard of Alibaba, 11.3pp more likely to have searched for goods on Alibaba, and 8.7pp more likely to have compared prices on Alibaba with prices from their regular supplier. However, they are no more likely to have actually made a purchase from Alibaba. The coefficient is 1.4pp and the standard errors are small enough to at least rule out modest to large effects.

Thus, the fact that our training significantly increases firms' knowledge of Alibaba and their likelihood of having experimented with it, yet has no effect on their propensity to actually buy inputs from it, is strong evidence against the hypothesis that the binding constraint is that firms

[28] The results turn out to be the same if we include firms that received the main treatments.

struggle to understand how to use the platform. While our experiment was not designed to directly test social media against formal platforms, we can speculate that the fact that firms clearly prefer social media as their main way of doing e-commerce likely reflects something deeper about how social media–in this context–relaxes frictions in a way that formal platforms do not.

# 6 Retailers vs Wholesalers

Our study contains both retailers and wholesalers. In particular, 33% of the sample have at least some wholesaler clients. These types of firms are quite different, and it was *ex ante* unclear we should expect direct connections to foreign suppliers via social media to be more relevant for retailers or wholesalers. Retailers are generally too small to travel, and thus their baseline technology to access foreign goods (in absence of social media) is typically to buy from local wholesalers. Retailers may benefit from direct connections if it allows them to access a greater set of varieties, or to get better prices by shortening the supply chain. Wholesalers, on the other hand, are significantly more likely to travel at baseline. However, travel is expensive, and if social media allows them to partially substitute for travel, then the implications for profit are large. We thus specified that we would examine this dimension of heterogeneity in our PAP, which is what we do in this section.

We report the indexes for the main outcomes in Table 6. We use the same specification as that used throughout the paper, except that we now interact each treatment indicator with an indicator for whether the firm has wholesale clients. Throughout the table, the standard errors on the interaction coefficients are very large, so at best we can speculate on these differences. For the Foreign Market Access outcomes in Columns 1 and 2, the results appear fairly similar across retailers and wholesalers. For the index on suppliers in Turkey, the interaction coefficients are roughly equal in magnitude to the retail coefficients, perhaps suggesting a larger effect for wholesalers. Finally, there are some differences in the profit and sales index: there are essentially no (detectable) effects for retailers, while for wholesalers the pattern replicates that from the overall sample.

We thus conclude that the treatment does improve the foreign market access of both retailers and wholesalers, as evidenced by the increase in both the horizontal and vertical outcomes. The increase in foreign suppliers thus suggests that retailers substitute away from their local suppliers, but, since their scale of operations is small and this process takes time, any increases in profits in the short to medium run are sufficiently small that we are unable to detect them. Wholesalers, on the other hand, see a large increase in profit. This may be because wholesalers buy and sell in large quantities, so a new supplier can have more immediate implications for profit, or it may be because they have saved on travel costs. While we do not know for sure which one is the case, in Appendix Table A6, we show results on indicators for whether the firm has travelled internationally for business in the past 3 months (collected in the followup survey). The effects for wholesalers are large in magnitude with a few significant coefficients, but the standard errors are also large so these effects should be thought of as suggestive at best.

# 7 Conclusion

We study the extent to which social media can reduce search and trust frictions in international trade. Finding and developing relationships with suppliers is a first order issue, and previous research has highlighted that these frictions may be large. Thus, if social media can meaningfully reduce these frictions, it is a first order issue to understand how and to what extent, both to understand the descriptive fact that firms use it ubiquitously to interact with suppliers and to guide policy aiming to improve business outcomes.

Our results suggest that social media can meaningfully reduce these frictions. First, we find that connecting firms with foreign suppliers via social media improves their access to foreign inputs, as shown by the results of our mystery shopping exercise. This is not *ex ante* obvious: instead of using social media to interact directly with suppliers abroad, firms could buy from a local wholesaler or travel abroad themselves. Yet, the fact that we find relatively large effects suggests that substantial search frictions are still present in both of these methods, and that direct connections via social media can meaningfully reduce them.

Our mystery shopping results are largely driven by relaxing the search friction. Ultimately, though, whether firms are able to realise this better foreign market access depends on whether these connections develop into real relationships. Our findings, using both survey data and mobile money data, suggest that this is more likely to happen among firms in the trust treatments. This suggests that trust frictions are present in this setting, and that using social media to share information and coordinate action can reduce them. Ultimately, we find that our treatments cause some firms to develop meaningful new relationships and increase profit.

The widespread use of social media suggests that there is substantial demand for e-commerce, so it may therefore seem puzzling why firms don't use formal platforms that are explicitly designed to alleviate search and trust frictions. The fact that our Alibaba training has no effect on their propensity to buy inputs from it suggests that the reason is more fundamental than simply lack of knowledge. The exact reasons for limited use seem like fruitful topics for future research, but, the fact that firms clearly prefer social media as their main way of doing e-commerce likely reflects something deeper about how social media–in this context–relaxes frictions in a way that formal platforms do not.

Taken together, our results show that search and trust frictions are large, and that social media can meaningfully reduce them. Moreover, it has the potential to change the structure of supply chains for some firms: retailers can import directly, and wholesalers can save on travel costs. Policies that improve smartphone access and mobile connectivity are therefore likely to benefit firms through this channel and to potentially reshape supply chains. Similarly, social media companies are already introducing e-commerce features onto their apps (e.g., better search features or better virtual storefronts), and this is likely to further these changes. Our results thus suggest that the rapidly developing digital landscape in lower and middle income countries is likely to lead to substantial benefits for small businesses and require researchers, policymakers, and organisations to update how they think about how firms find, learn about, and develop relationships with suppliers in these contexts.

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# Tables

Table 1: Access to Foreign Goods

| | Horizontal | Vertical | | | | Price |
|---|---|---|---|---|---|---|
| | Find Product $\geq$ 3 Criteria | High Quality Dummy | Quality Score (/50) | Made in Turkey | Index | Price (USD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Pooled* | | | | | | |
| Treatment | 0.090*** | 0.139* | -0.214 | 0.144** | 0.422*** | 1.027 |
| | (0.030) | (0.068) | (0.579) | (0.067) | (0.138) | (0.657) |
| *Panel B: Individual Treatments* | | | | | | |
| Search Only | 0.134*** | 0.196** | 0.624 | 0.151* | 0.512*** | 1.309 |
| | (0.038) | (0.083) | (0.725) | (0.083) | (0.167) | (0.815) |
| | [0.003] | [0.066] | [0.699] | [0.167] | [0.011] | [0.315] |
| Search + Types | 0.050 | 0.176** | 0.009 | 0.106 | 0.419** | 1.156 |
| | (0.037) | (0.086) | (0.869) | (0.084) | (0.180) | (0.774) |
| | [0.174] | [0.108] | [0.992] | [0.209] | [0.065] | [0.315] |
| Search + Actions | 0.102** | 0.095 | -0.942 | 0.153* | 0.370** | 1.339 |
| | (0.038) | (0.086) | (0.909) | (0.081) | (0.171) | (0.830) |
| | [0.024] | [0.411] | [0.678] | [0.167] | [0.066] | [0.315] |
| Search + Types + Actions | 0.075* | 0.090 | -0.547 | 0.166* | 0.381** | 0.287 |
| | (0.038) | (0.087) | (0.849) | (0.084) | (0.178) | (0.817) |
| | [0.092] | [0.411] | [0.738] | [0.167] | [0.066] | [0.723] |
| Control Mean | 0.357 | 0.431 | 43.064 | 0.477 | 0.000 | 19.990 |
| % Increase (Pooled) | 25.2% | 32.3% | -0.5% | 30.2% | N/A | 5.1% |
| Adjusted $R^2$ | 0.11 | 0.10 | 0.36 | 0.18 | 0.02 | 0.48 |
| $N$ | 1579 | 358 | 358 | 360 | 360 | 642 |

*Note*: $p$-values are computed using randomisation inference. Specifically, we compute the randomised randomisation-$t$ $p$-value from Young (2019) using 1000 reps. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. At the bottom of the table, we report the number of coefficients in Panel B for which the Romano-Wolf multiple-testing adjusted $p$-value is below 0.1, 0.05, and 0.01, respectively (Romano and Wolf, 2005). We also report conventional robust standard errors in parentheses. Panel A shows the coefficient from a regression on an indicator that pools all four treated groups. Panel B shows the coefficients corresponding to treatment indicators for each of the four treatment arms. All regressions include covariates selected by Double Lasso (Belloni, Chernozhukov, and Hansen, 2014), as well as the outcome measured at baseline (if available).

Column 1 is an indicator that is one if the merchant finds a good that matches at least 3 horizontal criteria, and is missing if the merchant never replied to the mystery shopper or was otherwise unreachable. Column 2 is an indicator for whether the good's quality score is above the median product-group quality score. Column 3 is the raw quality score. Column 4 is an indicator for whether the good is made in Turkey, primarily inferred based on whether the label says . See the text for full details of how this outcome is constructed. Column 5 is the Anderson (2008) index combining the vertical outcomes. Column 6 is the price in USD, which is only measured conditional on the firm finding a good matching at least three horizontal criteria.

Table 2: Supplier Relationships (Followup Survey)

| | Regular Suppliers in Turkey | | | Previous Suppliers | | |
|---|---|---|---|---|---|---|
| | Any Reg Sup in Turkey | Num Reg Sup in Turkey | Index | Num Reg Sup Total | Num Reg Sup in Senegal | Ended with Reg Sup |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Pooled (Equal Weight)* | | | | | | |
| Treatment | 0.039* | 0.084** | 0.136** | -0.037 | -0.147 | 0.056*** |
| | (0.021) | (0.033) | (0.062) | (0.157) | (0.160) | (0.021) |
| *Panel B: Individual Treatments* | | | | | | |
| Search Only | 0.029 | 0.091* | 0.116 | 0.046 | -0.060 | 0.051* |
| | (0.026) | (0.049) | (0.081) | (0.205) | (0.206) | (0.028) |
| Search + Types | 0.054** | 0.071 | 0.164* | -0.134 | -0.243 | 0.056** |
| | (0.028) | (0.045) | (0.085) | (0.217) | (0.216) | (0.028) |
| Search + Actions | 0.005 | 0.007 | 0.019 | -0.033 | -0.093 | 0.070** |
| | (0.026) | (0.040) | (0.078) | (0.191) | (0.191) | (0.029) |
| Search + Types + Actions | 0.067** | 0.169*** | 0.245*** | -0.027 | -0.193 | 0.049* |
| | (0.028) | (0.053) | (0.086) | (0.216) | (0.217) | (0.028) |
| *Panel C: Trust Combinations* | | | | | | |
| $\hat{\beta}_{\text{Types}}$ | 0.043** | 0.070* | 0.137** | -0.087 | -0.141 | -0.008 |
| | (0.020) | (0.038) | (0.062) | (0.160) | (0.157) | (0.021) |
| $\hat{\beta}_{\text{Actions}}$ | -0.005 | 0.007 | -0.008 | 0.014 | 0.008 | 0.006 |
| | (0.020) | (0.039) | (0.063) | (0.157) | (0.152) | (0.021) |
| Control Mean | 0.167 | 0.222 | 0.000 | 3.700 | 3.213 | 0.135 |
| % Increase (Pooled) | 23.3% | 38.0% | N/A | -1.0% | -4.6% | 41.7% |
| RW Sig Coefs at 10%, 5%, 1% | 1, 0, 0 | 1, 1, 1 | 1, 1, 0 | 0, 0, 0 | 0, 0, 0 | 1, 1, 0 |
| Adjusted $R^2$ | 0.19 | 0.17 | 0.01 | 0.36 | 0.36 | 0.09 |
| $N$ | 1680 | 1680 | 1680 | 1681 | 1681 | 1671 |

*Note*: $p$-values are computed using randomisation inference. Specifically, we compute the randomised randomisation-$t$ $p$-value from Young (2019) using 5000 reps. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. At the bottom of the table, we report the number of coefficients in Panel B for which the Romano-Wolf multiple-testing adjusted $p$-value is below 0.1, 0.05, and 0.01, respectively (Romano and Wolf, 2005). We also report conventional robust standard errors in parentheses. Panel A shows an equally-weighted linear combination of the coefficients in Panel B. Panel B shows the coefficients corresponding to treatment indicators for each of the four treatment arms. All regressions include covariates selected by Double Lasso (Belloni, Chernozhukov, and Hansen, 2014), as well as the outcome measured at baseline (if available). Panel C shows linear combinations of the coefficients in Panel B corresponding to the Types and Actions frictions. In particular, $\hat{\beta}_{\text{Types}} = 0.5(\hat{\beta}_{\text{Search + Types}} - \hat{\beta}_{\text{Search}}) + 0.5(\hat{\beta}_{\text{Search + Types + Actions}} - \hat{\beta}_{\text{Search + Actions}})$, and $\hat{\beta}_{\text{Actions}}$ is defined analogously.

Column 1 is 1 if the merchant says that they have a regular supplier in Turkey. Column 2 is the number of regular suppliers in Turkey. Column 3 is the Anderson (2008). Column 4 is the total number of regular suppliers. Column 5 is the number of regular suppliers in Senegal. Column 6 is 1 if the merchant has ended a relationship with a regular supplier in the past 3 months. A regular supplier is defined as a supplier from whom the merchant has made two or more orders with an intention of continuing the relationship.

Table 3: Order Value (Mobile Money Data)

| | Any Order | Value Post Mystery Shopping | | Total Value | |
|---|---|---|---|---|---|
| | Any Order | Order Value (OLS) | Order Value (Poisson) | Order Value (OLS) | Order Value (Poisson) |
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A: Pooled (Equal Weight)* | | | | | |
| Trust Treatment | -0.002 | 4.041** | 1.294* | 3.697 | 0.383 |
| | (0.020) | (1.792) | (0.476) | (2.686) | (0.274) |
| *Panel B: Individual Treatments* | | | | | |
| Search + Types | 0.001 | 1.827 | 0.820 | 2.211 | 0.249 |
| | (0.024) | (1.457) | (0.553) | (2.724) | (0.301) |
| Search + Actions | 0.005 | 6.156*** | 1.686** | 5.098 | 0.505 |
| | (0.024) | (2.693) | (0.501) | (3.660) | (0.325) |
| Search + Types + Actions | -0.014 | 4.139 | 1.377 | 3.782 | 0.397 |
| | (0.024) | (4.005) | (0.798) | (5.132) | (0.464) |
| *Panel C: Trust Combinations* | | | | | |
| $\hat{\beta}_{\text{Types}}$ | -0.009 | -0.095 | 0.256 | 0.447 | 0.070 |
| | (0.017) | (2.494) | (0.483) | (3.242) | (0.287) |
| $\hat{\beta}_{\text{Actions}}$ | -0.004 | 4.235* | 1.121* | 3.334 | 0.327 |
| | (0.017) | (2.430) | (0.474) | (3.181) | (0.283) |
| Control Mean | 0.134 | 1.400 | 2.097 | 7.765 | 8.595 |
| % Increase (Pooled) | -1.9% | 288.6% | 264.7% | 47.6% | 46.7% |
| RW Multiple Testing $p$-value | 0, 0, 0 | 1, 1, 0 | 1, 1, 0 | 0, 0, 0 | 0, 0, 0 |
| Adjusted $R^2$ | 0.06 | 0.01 | 0.21 | 0.02 | 0.17 |
| $N$ | 1500 | 1500 | 1018 | 1500 | 1359 |

*Note*: $p$-values are computed using randomisation inference. Specifically, we compute the randomised randomisation-$t$ $p$-value from Young (2019) using 1000 reps. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. At the bottom of the table, we report the number of coefficients in Panel B for which the Romano-Wolf multiple-testing adjusted $p$-value is below 0.1, 0.05, and 0.01, respectively (Romano and Wolf, 2005). We also report conventional robust standard errors in parentheses. Panel A shows an equally-weighted linear combination of the coefficients in Panel B. Panel B shows the coefficients corresponding to treatment indicators for each of the three treatment groups with trust treatments, where Search Only is the omitted category. All regressions include covariates selected by Double Lasso (Belloni, Chernozhukov, and Hansen, 2014), as well as the outcome measured at baseline (if available). Panel C shows linear combinations of the coefficients in Panel B corresponding to the Types and Actions frictions. In particular, $\hat{\beta}_{\text{Types}} = 0.5\hat{\beta}_{\text{Search + Types}} + 0.5(\hat{\beta}_{\text{Search + Types + Actions}} - \hat{\beta}_{\text{Search + Actions}})$, and $\hat{\beta}_{\text{Actions}}$ is defined analogously.

Column 1 is an indicator for whether the merchant ever ordered from a study supplier. Column 2 is the total value of orders. Column 3 is the total value of orders, analysed with Poisson regression. Column 4 is the total value of orders. Column 5 is the total value of orders, analysed with Poisson regression. Mystery shopping took place during the first 13 weeks of the study. All values are in USD.

Table 4: Profit and Sales

| | Raw | | | Winsorized (1%) | | |
|---|---|---|---|---|---|---|
| | Profit (USD) | Sales (USD) | Index | Profit (USD) | Sales (USD) | Index |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Pooled* | | | | | | |
| Treatment | 79.4** | 275.0** | 0.205** | 44.0* | 127.7 | 0.109 |
| | (31.1) | (110.7) | (0.081) | (22.4) | (80.1) | (0.070) |
| *Panel B: Individual Treatments* | | | | | | |
| Search Only | 30.5 | 341* | .226** | 20.4 | 164 | .129 |
| | (29.1) | (175) | (.115) | (25) | (109) | (.096) |
| | [.484] | [.129] | [.111] | [.647] | [.331] | [.394] |
| Search + Types | 49.7 | 113 | .056 | 30.5 | 68.9 | .029 |
| | (36.6) | (118) | (.096) | (31.3) | (98.5) | (.095) |
| | [.373] | [.564] | [.57] | [.647] | [.688] | [.878] |
| Search + Actions | 29 | 109 | .093 | 21.3 | 22.9 | .031 |
| | (28.2) | (113) | (.079) | (24.5) | (85.8) | (.076) |
| | [.484] | [.564] | [.401] | [.647] | [.799] | [.878] |
| Search + Types + Actions | 222*** | 554*** | .46*** | 112*** | 267** | .256** |
| | (79.6) | (232) | (.195) | (37.3) | (124) | (.112) |
| | [5.1e-03] | [.033] | [.044] | [9.1e-03] | [.1] | [.068] |
| Control Mean | 188.3 | 609.5 | 0.000 | 188.3 | 609.5 | 0.000 |
| % Increase (Pooled) | 42.2% | 45.1% | N/A | 23.4% | 20.9% | N/A |
| Adjusted $R^2$ | 0.19 | 0.23 | -0.01 | 0.34 | 0.35 | 0.00 |
| $N$ | 1351 | 1378 | 1431 | 1351 | 1378 | 1431 |

*Note*: $p$-values are computed using randomisation inference. Specifically, we compute the randomised randomisation-$t$ $p$-value from Young (2019) using 1000 reps. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. At the bottom of the table, we report the number of coefficients in Panel B for which the Romano-Wolf multiple-testing adjusted $p$-value is below 0.1, 0.05, and 0.01, respectively (Romano and Wolf, 2005). We also report conventional robust standard errors in parentheses. Panel A shows the coefficient from a regression on an indicator that pools all four treated groups. Panel B shows the coefficients corresponding to treatment indicators for each of the four treatment arms. All regressions include covariates selected by Double Lasso (Belloni, Chernozhukov, and Hansen, 2014), as well as the outcome measured at baseline (if available).

Column 1 is total profit from the past 30 days in USD. Column 2 is total sales from the past 30 days in USD. Column 3 is the Anderson (2008) index combining the previous two columns. Column 4 is total profit from the past 30 days in USD, winsorizing the top 1%. Column 5 is total sales from the past 30 days in USD, winsorizing the top 1%. Column 6 is the Anderson (2008) index combining the previous two columns. Profit is measured using the survey question from De Mel, McKenzie, and Woodruff (2009). Sales is measured using a similar survey question.

Table 5: Effect of Alibaba Training

| | Heard of Alibaba (1) | Searched on Alibaba (2) | Compared Prices with Supplier (3) | Bought on Alibaba (4) |
|---|---|---|---|---|
| e-Commerce Treatment | 0.065*** | 0.113** | 0.087* | 0.014 |
| | (0.025) | (0.052) | (0.049) | (0.035) |
| Control Mean | 0.908 | 0.423 | 0.319 | 0.135 |
| % Increase | 7.2% | 26.8% | 27.4% | 10.7% |
| Adjusted $R^2$ | 0.07 | 0.09 | 0.14 | 0.22 |
| $N$ | 340 | 340 | 340 | 340 |

*Note*: $p$-values are computed using randomisation inference. Specifically, we compute the randomised randomisation-$t$ $p$-value from Young (2019) using 5000 reps. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. Conventional robust standard errors are reported in parentheses. This table shows the effect of the Alibaba training treatment on Alibaba usage.

Table 6: Heterogeneity by Retailer vs Wholesaler

| | Horiz Dummy (1) | Vert Index (2) | Sup Turk Index (3) | Prof Sales Index (1%) (4) |
|---|---|---|---|---|
| Search Only | 0.194*** | 0.382* | 0.059 | -0.004 |
| | (0.047) | (0.195) | (0.094) | (0.088) |
| Search + Types | 0.049 | 0.315 | 0.183* | -0.010 |
| | (0.047) | (0.208) | (0.097) | (0.089) |
| Search + Actions | 0.131*** | 0.286 | -0.017 | 0.033 |
| | (0.047) | (0.207) | (0.091) | (0.071) |
| Search + Types + Actions | 0.036 | 0.281 | 0.165 | 0.026 |
| | (0.049) | (0.229) | (0.103) | (0.081) |
| S Only * Wholesaler | -0.158* | 0.106 | 0.134 | 0.308 |
| | (0.083) | (0.420) | (0.188) | (0.250) |
| S + T * Wholesaler | 0.048 | 0.024 | -0.027 | 0.146 |
| | (0.083) | (0.404) | (0.184) | (0.260) |
| S + A * Wholesaler | -0.024 | -0.007 | 0.106 | -0.053 |
| | (0.084) | (0.419) | (0.179) | (0.222) |
| S + T + A * Wholesaler | 0.114 | 0.087 | 0.155 | 0.666** |
| | (0.083) | (0.421) | (0.189) | (0.290) |
| Control Mean Retail | 0.374 | -0.006 | 0.003 | 0.077 |
| Control Mean Wholesale | 0.315 | 0.019 | -0.007 | -0.192 |
| Adjusted $R^2$ | 0.01 | -0.01 | 0.00 | 0.01 |
| $N$ | 1579 | 351 | 1680 | 1431 |

*Note*: This table shows the main results with treatment interacted with an indicator for whether a firm sells wholesale.

# Figures

Figure 1: Supplier WhatsApp Groups

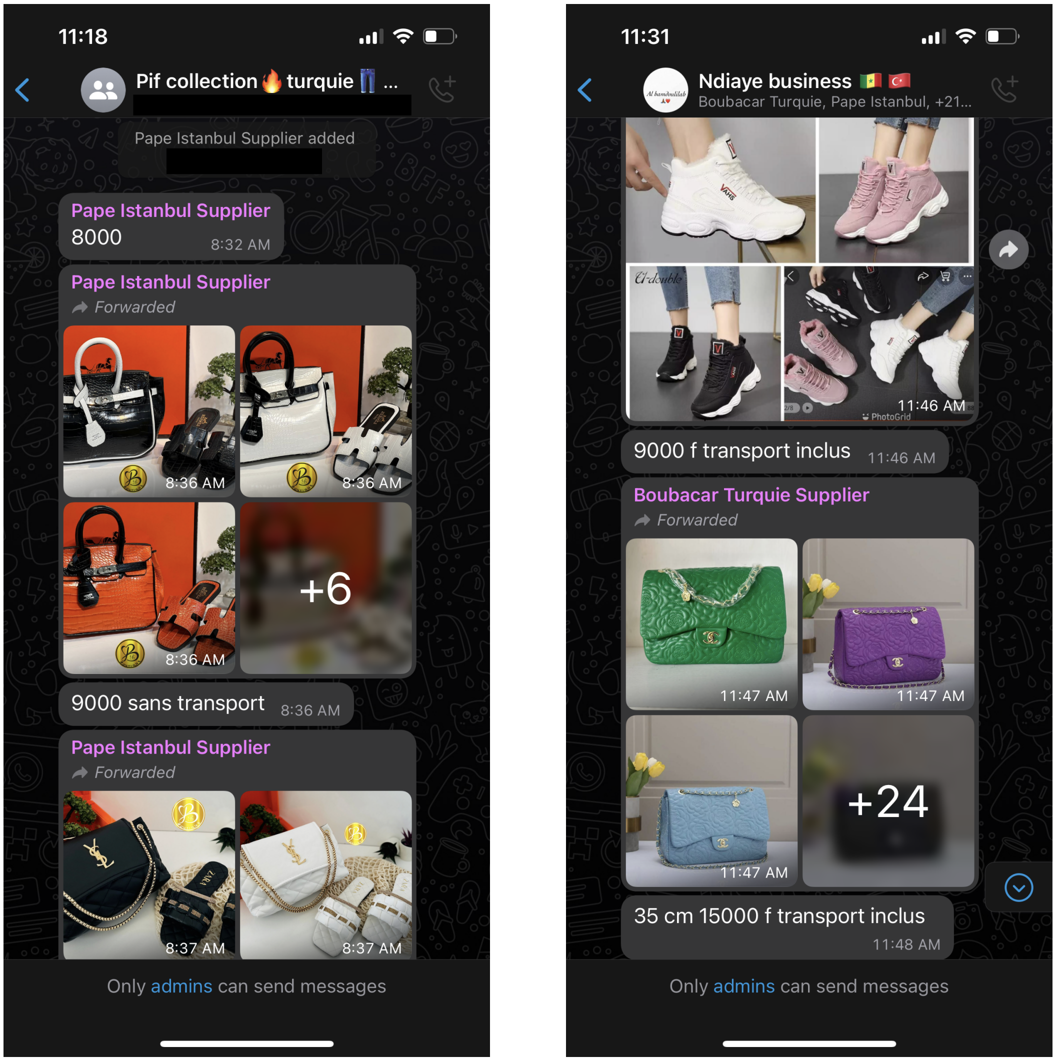
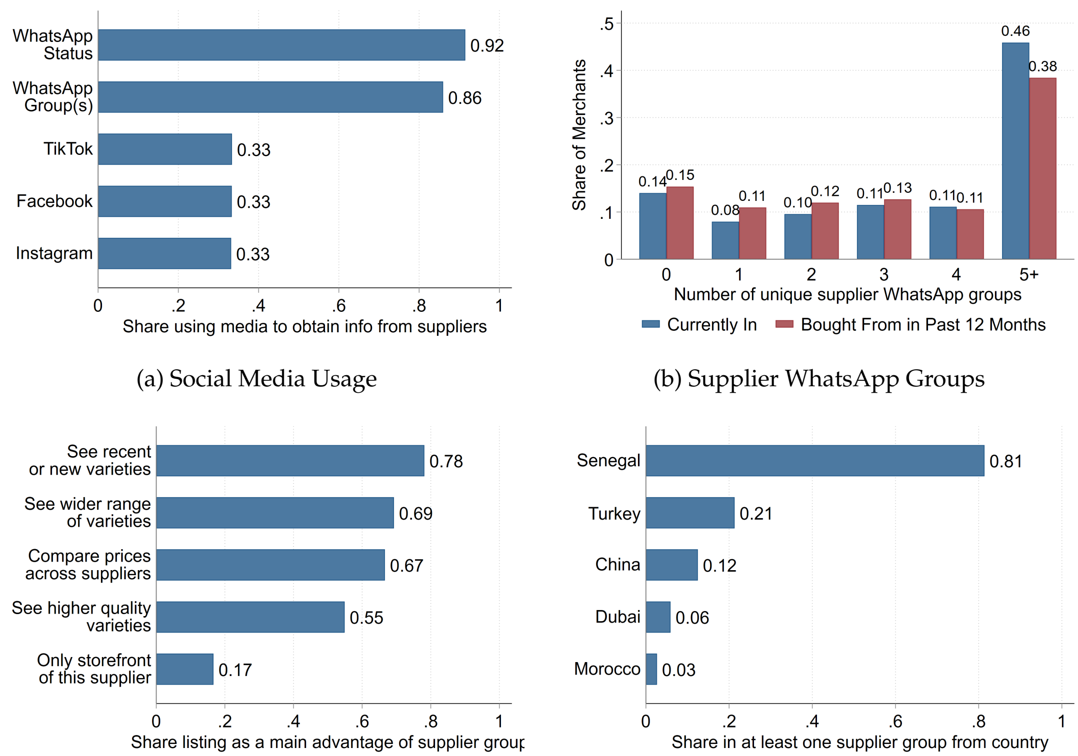


Figure 2: Firm Social Media Usage to obtain Information about Suppliers




(a) Social Media Usage

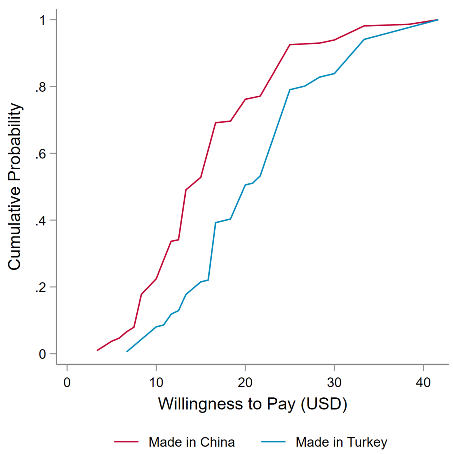
(b) Supplier WhatsApp Groups

(c) Advantages of Supplier Groups

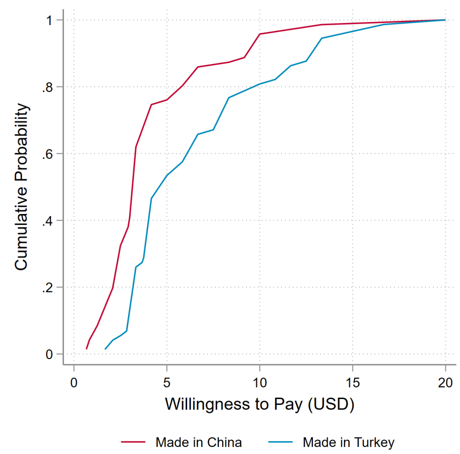
(d) Supplier Groups, by Supplier Country

*Note*: This figure shows a number of statistics about how firms in our sample use social media to obtain information about suppliers. All data is from our baseline survey with 1862 firms. Panel (a) shows the results of a question asking firms to select all social media that they use to obtain information about suppliers for their business. Panel (b) shows the distribution of the number of supplier WhatsApp groups a firm is in at the time of the baseline survey, as well as the distribution of the number of such groups that the firm has directly made at least one purchase from in the past 12 months. Supplier WhatsApp groups are defined as WhatsApp groups in which the primary purpose is for suppliers to advertise their wares to downstream clients. Panel (c) shows the results of a question asking firms that use supplier WhatsApp groups to select all reasons why they find these groups useful. Panel (d) shows the share of firms who are in at least one supplier WhatsApp group where the supplier located and based in the country listed.

Figure 3: Willingness to Pay by Product Origin




(a) Consumer Survey ($N = 400$)




(b) Firm Survey ($N = 144$)

*Note*: This figure shows the results of two exercises in which we showed various images of garments to survey respondants, randomised whether we said the good was made in Turkey or made in China, and elicited willingness to pay for the garments. Panel (a) shows the CDF of WTP in the consumer survey, separately by whether we said the good was made in Turkey or China. The distribution is truncated at 40 USD for ease of readability. Panel (b) shows the CDF of WTP for a small, separate survey of firms (for a different set of goods), with distribution truncated at 20 USD for ease of readability.

Figure 4: Design Tree

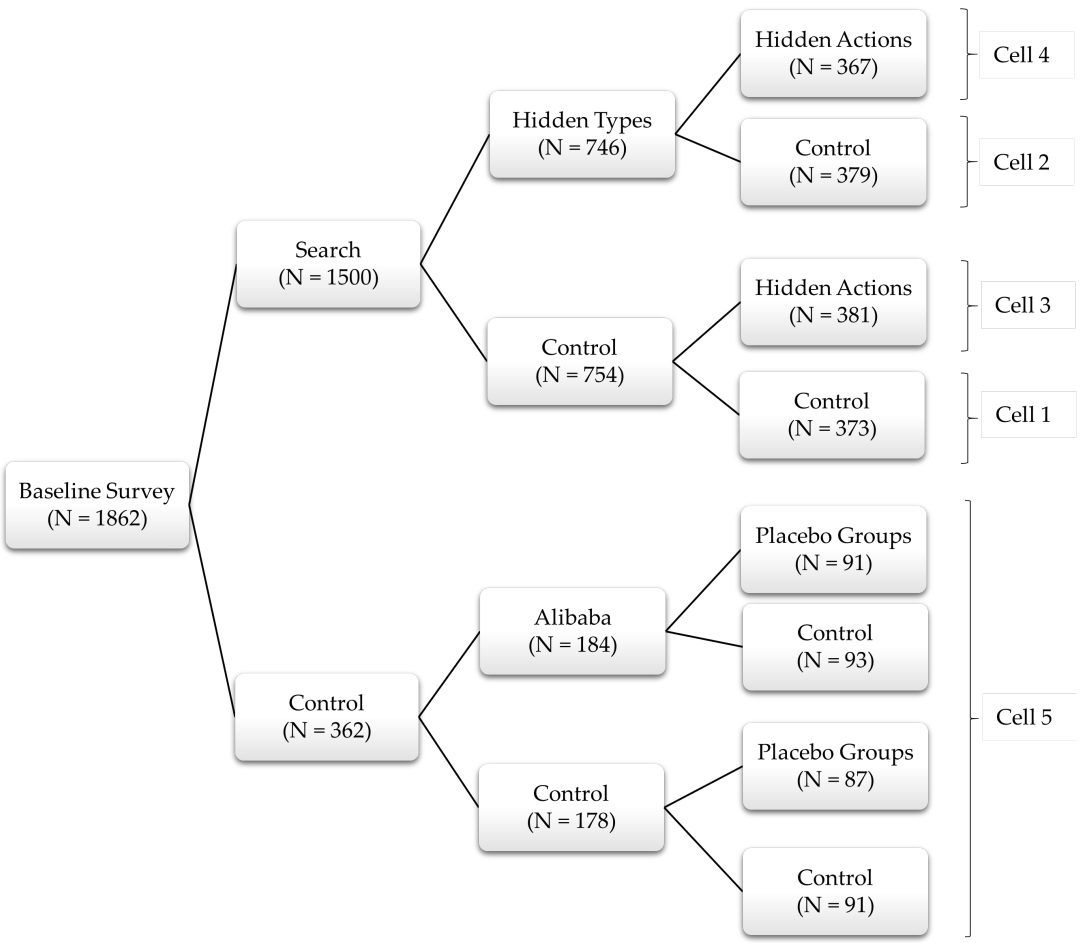
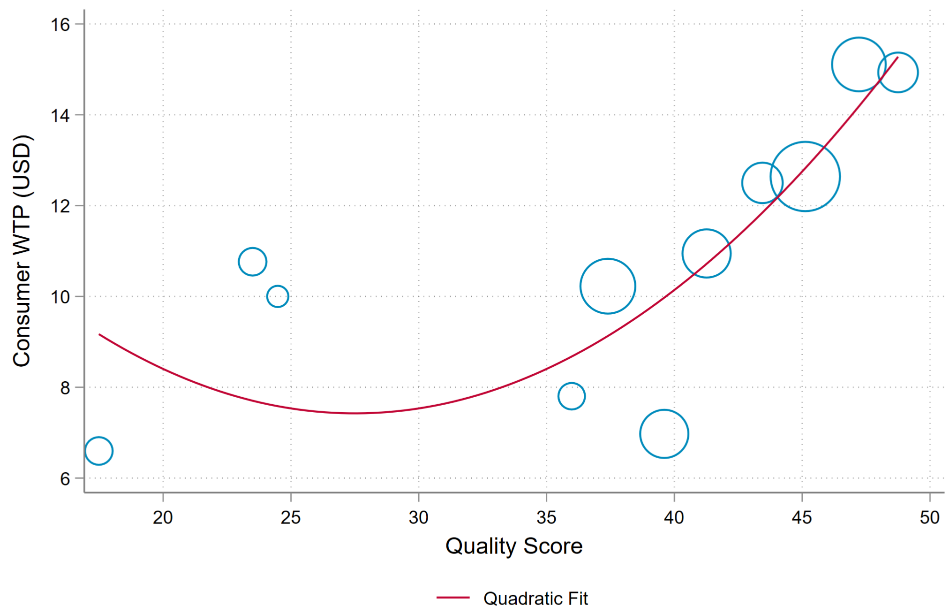
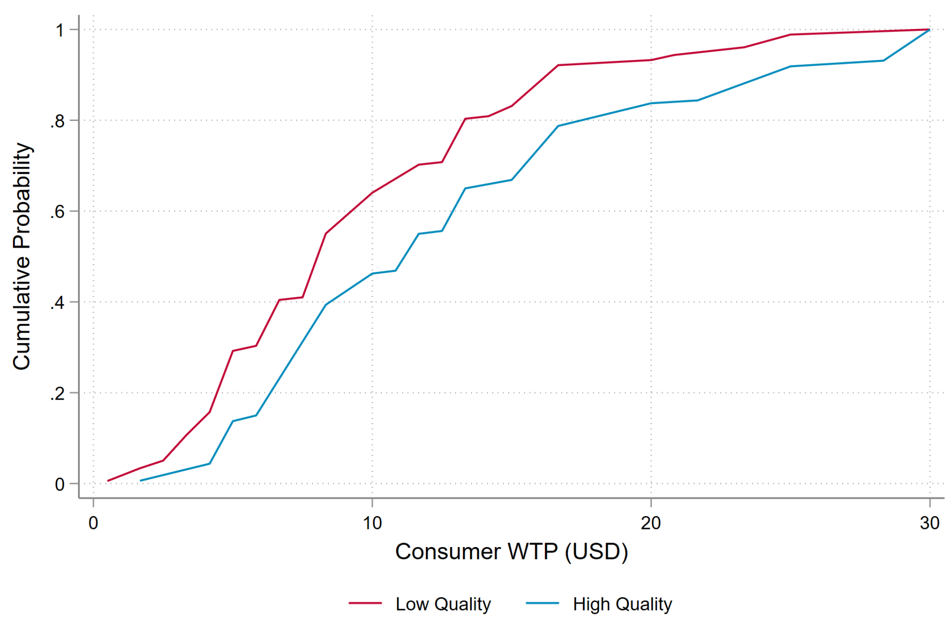


Figure 5: Consumer Willingness to Pay for Quality



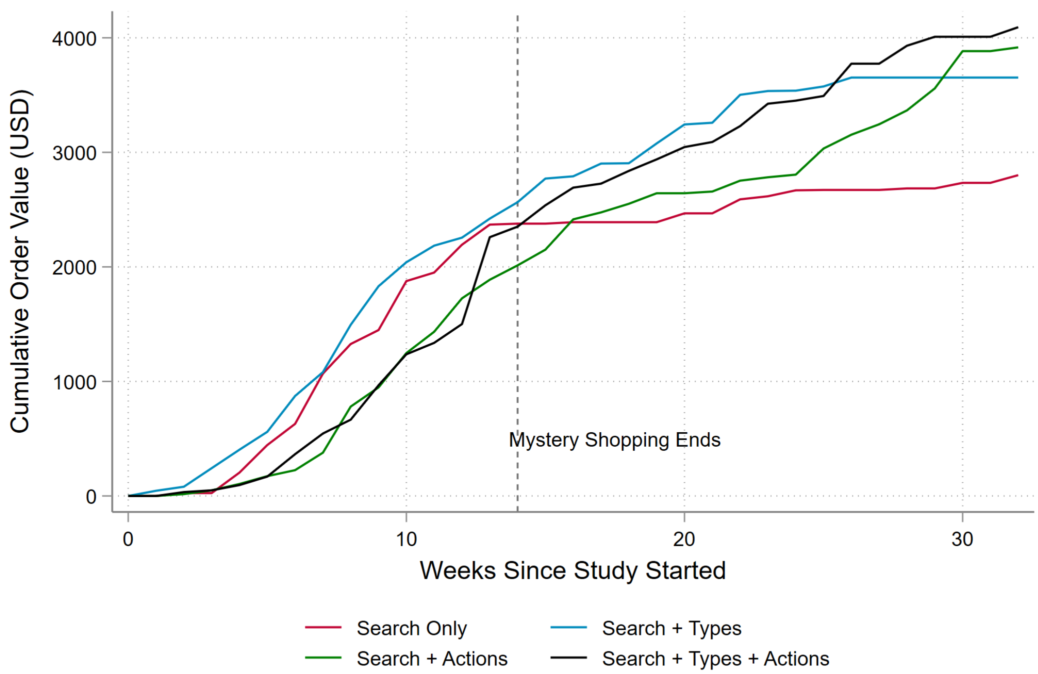

(a) Raw Score




(b) CDF of WTP by High or Low Quality

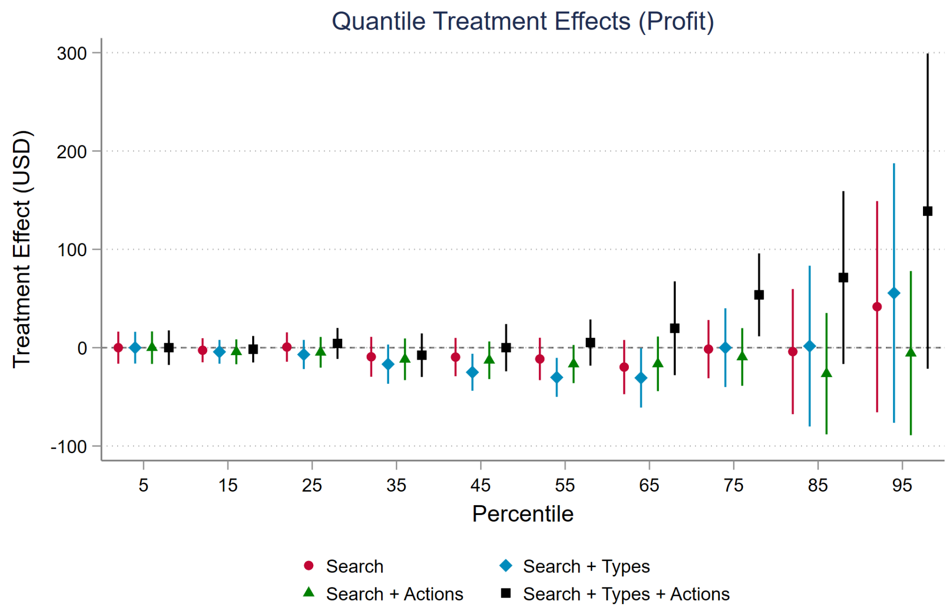
*Note*: Panel (a) shows a binscatter of consumer willingness to pay for garments (as measured by the consumer survey) against the quality score of the garments. The size of each bubble is proportional to the number of observations. Panel (b) shows the CDF of consumer willingness to pay separately based on whether the garment met our definition of high quality. We truncate willingness to pay at 30 USD to avoid unnecessarily stretching the x-axis. See the main text for full details on the consumer survey and variable construction.

Figure 6: Cumulative Order Value (Mobile Money Data)

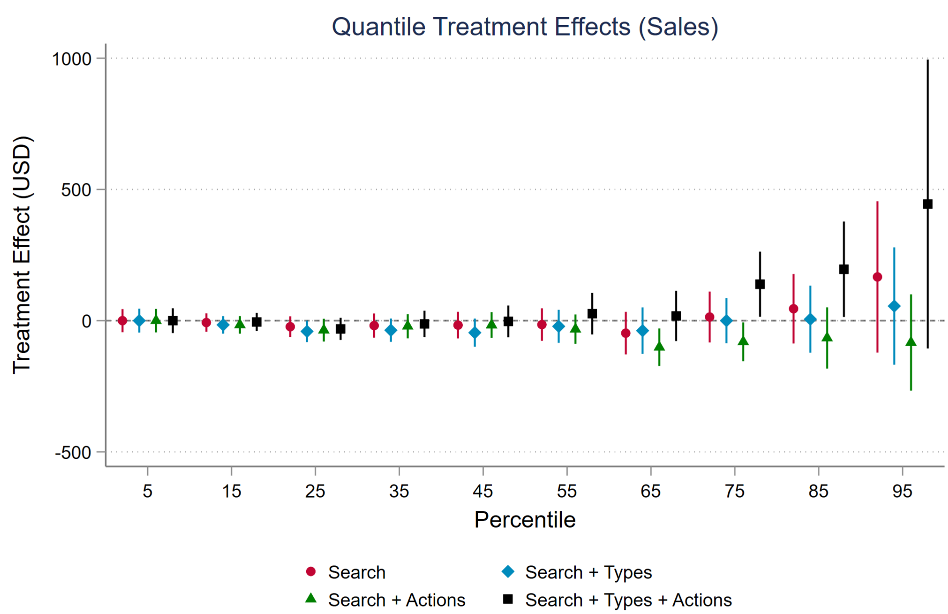



*Note*: This figure shows the total order value from study suppliers, according to the mobile money data, in each treatment group as a function of number of weeks since the study begun (16 November 2023). Pure control is omitted as they were not connected to any study suppliers.

Figure 7: Quantile Treatment Effects




(a) Profit




(b) Sales

*Note*: This figure shows the coefficients from quantile regressions of profit and sales on the four treatment groups. All quantile regressions include the outcome measured at baseline (if available), but otherwise do not include any covariates. We plot 95% confidence intervals constructed using randomisation inference, defined as the set of sharp nulls that do not reject at the 5% level.

# Appendix

## Tables

Table A1: Balance Table

| Variable | Control (1) | Search (2) | Search Types (3) | Search Actions (4) | Search Types Actions (5) | Joint $p$-value (6) |
|---|---|---|---|---|---|---|
| Female | 0.49 | 0.51 | 0.49 | 0.53 | 0.49 | 0.74 |
| Online Only | 0.67 | 0.66 | 0.68 | 0.7 | 0.65 | 0.56 |
| Business Age | 4.85 | 4.74 | 5.2 | 4.72 | 5.21 | 0.57 |
| Share Cust Turkey | 0.43 | 0.45 | 0.45 | 0.44 | 0.45 | 0.96 |
| Any Reg Supp Turkey | 0.22 | 0.21 | 0.24 | 0.21 | 0.19 | 0.67 |
| Travelled Business (5y) | 0.09 | 0.08 | 0.11 | 0.09 | 0.11 | 0.43 |
| Profit USD (30 Days) | 221.35 | 221.08 | 262.49 | 195.36 | 235.63 | 0.24 |
| Bought Alibaba Ever | 0.16 | 0.13 | 0.15 | 0.18 | 0.13 | 0.23 |
| $N$ | 362 | 373 | 379 | 381 | 367 | |

*Note*: The table shows the mean for each variable in each of the five treatment cells. The final column shows the $p$-value from regressing the variable on indicators for each treatment (where the control group is omitted) and conducting a test that all coefficients are zero. Finally, we run a multinomial logit of treatment group against all of the variables in the table, for which a joint test that all coefficients are zero has a $p$-value of .

Table A2: Horizontal Outcomes (Detailed)

| | Extensive vs Intensive Margin | | Number of Criteria | |
|---|---|---|---|---|
| | Agree Search | Find Product Conditional | Num Criteria Unconditional | Num Criteria Conditional |
| | (1) | (2) | (3) | (4) |
| *Panel A: Pooled (Equal Weight)* | | | | |
| Treatment | 0.022 | 0.095*** | 0.356*** | 0.358** |
| | (0.024) | (0.035) | (0.122) | (0.137) |
| *Panel B: Individual Treatments* | | | | |
| Search Only | 0.021 | 0.144*** | 0.657*** | 0.730*** |
| | (0.029) | (0.043) | (0.159) | (0.175) |
| Search + Types | 0.010 | 0.064 | 0.159 | 0.165 |
| | (0.029) | (0.043) | (0.156) | (0.177) |
| Search + Actions | 0.033 | 0.096** | 0.377** | 0.325* |
| | (0.029) | (0.043) | (0.157) | (0.172) |
| Search + Types + Actions | 0.026 | 0.076* | 0.231 | 0.211 |
| | (0.030) | (0.044) | (0.156) | (0.176) |
| *Panel C: Trust Combinations* | | | | |
| $\hat{\beta}_{\text{Types}}$ | -0.009 | -0.050* | -0.322*** | -0.339*** |
| | (0.020) | (0.030) | (0.114) | (0.126) |
| $\hat{\beta}_{\text{Actions}}$ | 0.014 | -0.018 | -0.104 | -0.179 |
| | (0.020) | (0.030) | (0.114) | (0.126) |
| Control Mean | 0.781 | 0.457 | 1.650 | 2.111 |
| % Increase (Pooled) | 2.8% | 20.8% | 21.6% | 17.0% |
| RW Sig Coefs at 10%, 5%, 1% | 0, 0, 0 | 2, 1, 1 | 2, 2, 1 | 1, 1, 1 |
| Adjusted $R^2$ | 0.21 | 0.07 | 0.09 | 0.08 |
| $N$ | 1579 | 1269 | 1579 | 1269 |

*Note*: $p$-values are computed using randomisation inference. Specifically, we compute the randomised randomisation-$t$ $p$-value from Young (2019) using 5000 reps. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. At the bottom of the table, we report the number of coefficients in Panel B for which the Romano-Wolf multiple-testing adjusted $p$-value is below 0.1, 0.05, and 0.01, respectively (Romano and Wolf, 2005). We also report conventional robust standard errors in parentheses. Panel A shows an equally-weighted linear combination of the coefficients in Panel B. Panel B shows the coefficients corresponding to treatment indicators for each of the four treatment arms. All regressions include covariates selected by Double Lasso (Belloni, Chernozhukov, and Hansen, 2014), as well as the outcome measured at baseline (if available). Panel C shows linear combinations of the coefficients in Panel B corresponding to the Types and Actions frictions. In particular, $\hat{\beta}_{\text{Types}} = 0.5(\hat{\beta}_{\text{Search + Types}} - \hat{\beta}_{\text{Search}}) + 0.5(\hat{\beta}_{\text{Search + Types + Actions}} - \hat{\beta}_{\text{Search + Actions}})$, and $\hat{\beta}_{\text{Actions}}$ is defined analogously.

Column 1 is 1 if the merchant agrees to sell or search for the product, and is missing if the merchant never replied to the mystery shopper or was otherwise unreachable. Column 2 is 1 if the merchant found a suitable product, conditional on agreeing to sell or search for the product. Column 3 is the number of horizontal criteria of the product, and is 0 if the merchant either did not agree to sell or search for a product or agreed but never sent any product. Column 4 is the number of horizontal criteria of the product, conditional on agreeing to sell or search for a product, and is 0 if the merchant agreed but never sent any product.

Table A3: Vertical Outcomes (Detailed)

| | From Turkey | | |
|---|---|---|---|
| | Made in Turkey (Label) | Made in Turkey (Tailor Judgement) | Made in Turkey (Label + Tailors) |
| | (1) | (2) | (3) |
| *Panel A: Pooled (Equal Weight)* | | | |
| Treatment | 0.126 | 0.176** | 0.114 |
| | (0.080) | (0.085) | (0.070) |
| *Panel B: Individual Treatments* | | | |
| Search Only | 0.083 | 0.265*** | 0.113 |
| | (0.097) | (0.097) | (0.083) |
| Search + Types | 0.100 | 0.104 | 0.078 |
| | (0.092) | (0.108) | (0.088) |
| Search + Actions | 0.130 | 0.213** | 0.119 |
| | (0.092) | (0.096) | (0.083) |
| Search + Types + Actions | 0.192** | 0.123 | 0.148* |
| | (0.094) | (0.098) | (0.085) |
| *Panel C: Trust Combinations* | | | |
| $\hat{\beta}_{\text{Types}}$ | 0.040 | -0.125** | -0.003 |
| | (0.055) | (0.060) | (0.055) |
| $\hat{\beta}_{\text{Actions}}$ | 0.070 | -0.017 | 0.038 |
| | (0.057) | (0.061) | (0.056) |
| Control Mean | 0.500 | 0.585 | 0.554 |
| % Increase (Pooled) | 25.3% | 30.1% | 20.6% |
| RW Sig Coefs at 10%, 5%, 1% | 0, 0, 0 | 2, 1, 0 | 0, 0, 0 |
| Adjusted $R^2$ | 0.31 | 0.14 | 0.11 |
| $N$ | 252 | 284 | 328 |

*Note*: $p$-values are computed using randomisation inference. Specifically, we compute the randomised randomisation-$t$ $p$-value from Young (2019) using 5000 reps. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. At the bottom of the table, we report the number of coefficients in Panel B for which the Romano-Wolf multiple-testing adjusted $p$-value is below 0.1, 0.05, and 0.01, respectively (Romano and Wolf, 2005). We also report conventional robust standard errors in parentheses. Panel A shows an equally-weighted linear combination of the coefficients in Panel B. Panel B shows the coefficients corresponding to treatment indicators for each of the four treatment arms. All regressions include covariates selected by Double Lasso (Belloni, Chernozhukov, and Hansen, 2014), as well as the outcome measured at baseline (if available). Panel C shows linear combinations of the coefficients in Panel B corresponding to the Types and Actions frictions. In particular, $\hat{\beta}_{\text{Types}} = 0.5(\hat{\beta}_{\text{Search + Types}} - \hat{\beta}_{\text{Search}}) + 0.5(\hat{\beta}_{\text{Search + Types + Actions}} - \hat{\beta}_{\text{Search + Actions}})$, and $\hat{\beta}_{\text{Actions}}$ is defined analogously.

Column 1 is 1 if the label says , 0 if the label says for X other than Turkey, and missing otherwise. Column 2 is 1 if both tailors independently determined that the product was made in Turkey, and is 0 if both tailors independently determined that the product was not made in Turkey. It is missing if the tailors disagreed. For shoes, as there was only one expert shoemaker, we take their opinion directly. Column 3 is an indicator that combines the label and tailor measures of whether the good was made in Turkey. It is equal to the label measure where available, and the tailor measure otherwise.

Table A4: Supplier Relationships (Further Results on Substitution)

| | Reg Supp in China | | Media for Suppliers | | | Forward Media | |
|---|---|---|---|---|---|---|---|
| | Any Supp in China | Num Supp in China | Uses Facebook | Uses TikTok | Uses Instagram | Fwd Photo for Search | Fwd Photo for Price |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Panel A: Pooled (Equal Weight)* | | | | | | | |
| Treatment | -0.025 | -0.015 | -0.074*** | -0.023 | -0.015 | -0.058** | -0.087*** |
| | (0.016) | (0.035) | (0.027) | (0.025) | (0.026) | (0.027) | (0.030) |
| *Panel B: Individual Treatments* | | | | | | | |
| Search Only | -0.025 | -0.018 | -0.081** | -0.046 | -0.021 | -0.056 | -0.088** |
| | (0.019) | (0.040) | (0.033) | (0.031) | (0.032) | (0.036) | (0.038) |
| Search + Types | -0.032* | -0.040 | -0.055 | 0.004 | -0.037 | -0.048 | -0.080** |
| | (0.019) | (0.042) | (0.033) | (0.031) | (0.032) | (0.034) | (0.038) |
| Search + Actions | -0.015 | 0.019 | -0.071** | -0.036 | 0.004 | -0.060* | -0.065* |
| | (0.019) | (0.043) | (0.033) | (0.031) | (0.033) | (0.034) | (0.038) |
| Search + Types + Actions | -0.028 | -0.021 | -0.089*** | -0.014 | -0.007 | -0.069* | -0.113*** |
| | (0.020) | (0.044) | (0.033) | (0.033) | (0.033) | (0.035) | (0.038) |
| *Panel C: Trust Combinations* | | | | | | | |
| $\hat{\beta}_{\text{Types}}$ | -0.010 | -0.031 | 0.004 | 0.036 | -0.013 | 0.000 | -0.020 |
| | (0.012) | (0.027) | (0.022) | (0.023) | (0.022) | (0.025) | (0.028) |
| $\hat{\beta}_{\text{Actions}}$ | 0.007 | 0.028 | -0.012 | -0.004 | 0.027 | -0.013 | -0.005 |
| | (0.012) | (0.028) | (0.022) | (0.023) | (0.022) | (0.025) | (0.028) |
| Control Mean | 0.099 | 0.167 | 0.328 | 0.290 | 0.279 | 0.716 | 0.659 |
| % Increase (Pooled) | -25.4% | -9.0% | -22.5% | -7.9% | -5.5% | -8.1% | -13.1% |
| RW Sig Coefs at 10%, 5%, 1% | 0, 0, 0 | 0, 0, 0 | 3, 2, 0 | 0, 0, 0 | 0, 0, 0 | 0, 0, 0 | 4, 1, 0 |
| Adjusted $R^2$ | 0.22 | 0.42 | 0.12 | 0.15 | 0.15 | 0.08 | 0.07 |
| $N$ | 1680 | 1680 | 1671 | 1671 | 1671 | 1671 | 1565 |

*Note*: $p$-values are computed using randomisation inference. Specifically, we compute the randomised randomisation-$t$ $p$-value from Young (2019) using 5000 reps. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. At the bottom of the table, we report the number of coefficients in Panel B for which the Romano-Wolf multiple-testing adjusted $p$-value is below 0.1, 0.05, and 0.01, respectively (Romano and Wolf, 2005). We also report conventional robust standard errors in parentheses. Panel A shows an equally-weighted linear combination of the coefficients in Panel B. Panel B shows the coefficients corresponding to treatment indicators for each of the four treatment arms. All regressions include covariates selected by Double Lasso (Belloni, Chernozhukov, and Hansen, 2014), as well as the outcome measured at baseline (if available). Panel C shows linear combinations of the coefficients in Panel B corresponding to the Types and Actions frictions. In particular, $\hat{\beta}_{\text{Types}} = 0.5(\hat{\beta}_{\text{Search + Types}} - \hat{\beta}_{\text{Search}}) + 0.5(\hat{\beta}_{\text{Search + Types + Actions}} - \hat{\beta}_{\text{Search + Actions}})$, and $\hat{\beta}_{\text{Actions}}$ is defined analogously.

Column 1 is 1 if the merchant says that they have a regular supplier in China. Column 2 is 1 if the merchant says that they have a regular supplier in China. Column 3 is 1 if the merchant says that they use Facebook to learn about suppliers. Column 4 is 1 if the merchant says that they use TikTok to learn about suppliers. Column 5 is 1 if the merchant says that they use Instagram to learn about suppliers. Column 6 is 1 if the merchant says that they have forwarded a photo or video from a supplier group to a regular supplier to try to obtain a similar product in the past 3 months. Column 7 is 1 if the merchant says that they have forwarded a photo or video from a supplier group to a regular supplier to try to obtain a better price in the past 3 months. A regular supplier is defined as a supplier from whom the merchant has made two or more orders with an intention of continuing the relationship.

Table A5: Profit and Sales (Poisson Regression)

| | Profit | | Sales | |
|---|---|---|---|---|
| | Profit 30 Days (USD) | Profit 30 Days Winsorized 1% (USD) | Sales 30 Days (USD) | Sales 30 Days Winsorized 1% (USD) |
| | (1) | (2) | (3) | (4) |
| *Panel A: Pooled (Equal Weight)* | | | | |
| Treatment | 0.240* | 0.091 | 0.141 | 0.082 |
| | (0.112) | (0.095) | (0.113) | (0.110) |
| *Panel B: Individual Treatments* | | | | |
| Search Only | 0.169 | 0.055 | 0.308* | 0.213 |
| | (0.135) | (0.124) | (0.151) | (0.143) |
| Search + Types | 0.138 | 0.037 | -0.054 | -0.026 |
| | (0.161) | (0.134) | (0.167) | (0.151) |
| Search + Actions | 0.037 | -0.033 | -0.106 | -0.102 |
| | (0.130) | (0.112) | (0.140) | (0.130) |
| Search + Types + Actions | 0.616*** | 0.307** | 0.417* | 0.243 |
| | (0.184) | (0.130) | (0.201) | (0.151) |
| *Panel C: Trust Combinations* | | | | |
| $\hat{\beta}_{\text{Types}}$ | 0.274* | 0.161 | 0.080 | 0.052 |
| | (0.126) | (0.095) | (0.127) | (0.108) |
| $\hat{\beta}_{\text{Actions}}$ | 0.173 | 0.091 | 0.029 | -0.023 |
| | (0.115) | (0.093) | (0.139) | (0.111) |
| Control Mean | 187.7 | 187.7 | 609.5 | 609.5 |
| % Increase (Pooled) | 27.1% | 9.5% | 15.1% | 8.5% |
| RW Sig Coefs at 10%, 5%, 1% | 1, 1, 0 | 0, 0, 0 | 0, 0, 0 | 0, 0, 0 |
| Adjusted $R^2$ | 0.49 | 0.47 | 0.56 | 0.52 |
| $N$ | 1351 | 1351 | 1378 | 1378 |

*Note*: $p$-values are computed using randomisation inference. Specifically, we compute the randomised randomisation-$t$ $p$-value from Young (2019) using 5000 reps. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. At the bottom of the table, we report the number of coefficients in Panel B for which the Romano-Wolf multiple-testing adjusted $p$-value is below 0.1, 0.05, and 0.01, respectively (Romano and Wolf, 2005). We also report conventional robust standard errors in parentheses. Panel A shows an equally-weighted linear combination of the coefficients in Panel B. Panel B shows the coefficients corresponding to treatment indicators for each of the four treatment arms. All regressions include covariates selected by Double Lasso (Belloni, Chernozhukov, and Hansen, 2014), as well as the outcome measured at baseline (if available). Panel C shows linear combinations of the coefficients in Panel B corresponding to the Types and Actions frictions. In particular, $\hat{\beta}_{\text{Types}} = 0.5(\hat{\beta}_{\text{Search + Types}} - \hat{\beta}_{\text{Search}}) + 0.5(\hat{\beta}_{\text{Search + Types + Actions}} - \hat{\beta}_{\text{Search + Actions}})$, and $\hat{\beta}_{\text{Actions}}$ is defined analogously.

Column 1 is total profit from the past 30 days in USD. Column 2 is total profit from the past 30 days in USD, winsorizing the top 1%. Column 3 is total sales from the past 30 days in USD. Column 4 is total sales from the past 30 days in USD, winsorizing the top 1%. Profit is measured using the survey question from De Mel, McKenzie, and Woodruff (2009). Sales is measured using a similar survey question.

Table A6: Travel

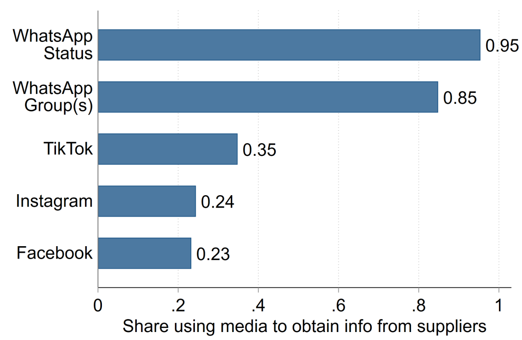
| | Wholesalers | | | Retailers | | |
|---|---|---|---|---|---|---|
| | Any Travel | Travel China | Travel Turkey | Any Travel | Travel China | Travel Turkey |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Pooled (Equal Weight)* | | | | | | |
| Treatment | -0.030 | -0.020 | -0.020 | -0.007 | -0.019 | 0.003 |
| | (0.032) | (0.026) | (0.020) | (0.014) | (0.011) | (0.005) |
| *Panel B: Individual Treatments* | | | | | | |
| Search Only | 0.003 | 0.008 | -0.025 | -0.009 | -0.021 | -0.005 |
| | (0.044) | (0.035) | (0.026) | (0.018) | (0.013) | (0.004) |
| Search + Types | -0.005 | -0.002 | -0.014 | -0.005 | -0.023** | 0.005 |
| | (0.039) | (0.031) | (0.023) | (0.017) | (0.011) | (0.008) |
| Search + Actions | -0.065* | -0.051* | -0.024 | -0.012 | -0.013 | 0.010 |
| | (0.034) | (0.028) | (0.020) | (0.017) | (0.013) | (0.008) |
| Search + Types + Actions | -0.054 | -0.033 | -0.019 | -0.002 | -0.019 | 0.001 |
| | (0.033) | (0.027) | (0.020) | (0.019) | (0.013) | (0.006) |
| *Panel C: Trust Combinations* | | | | | | |
| $\hat{\beta}_{\text{Types}}$ | 0.002 | 0.003 | 0.008 | 0.007 | -0.004 | 0.000 |
| | (0.024) | (0.018) | (0.012) | (0.013) | (0.007) | (0.005) |
| $\hat{\beta}_{\text{Actions}}$ | -0.059** | -0.045** | -0.001 | 0.000 | 0.006 | 0.006 |
| | (0.024) | (0.018) | (0.013) | (0.013) | (0.008) | (0.006) |
| Control Mean | 0.130 | 0.090 | 0.040 | 0.041 | 0.033 | 0.004 |
| % Increase (Pooled) | -23.3% | -21.7% | -51.1% | -17.3% | -57.9% | 69.7% |
| RW Sig Coefs at 10%, 5%, 1% | 0, 0, 0 | 0, 0, 0 | 0, 0, 0 | 0, 0, 0 | 0, 0, 0 | 0, 0, 0 |
| Adjusted $R^2$ | 0.28 | 0.39 | 0.07 | 0.05 | 0.07 | 0.01 |
| $N$ | 546 | 546 | 546 | 1125 | 1125 | 1125 |

*Note*: $p$-values are computed using randomisation inference. Specifically, we compute the randomised randomisation-$t$ $p$-value from Young (2019) using 5000 reps. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. At the bottom of the table, we report the number of coefficients in Panel B for which the Romano-Wolf multiple-testing adjusted $p$-value is below 0.1, 0.05, and 0.01, respectively (Romano and Wolf, 2005). We also report conventional robust standard errors in parentheses. Panel A shows an equally-weighted linear combination of the coefficients in Panel B. Panel B shows the coefficients corresponding to treatment indicators for each of the four treatment arms. All regressions include covariates selected by Double Lasso (Belloni, Chernozhukov, and Hansen, 2014), as well as the outcome measured at baseline (if available). Panel C shows linear combinations of the coefficients in Panel B corresponding to the Types and Actions frictions. In particular, $\hat{\beta}_{\text{Types}} = 0.5(\hat{\beta}_{\text{Search + Types}} - \hat{\beta}_{\text{Search}}) + 0.5(\hat{\beta}_{\text{Search + Types + Actions}} - \hat{\beta}_{\text{Search + Actions}})$, and $\hat{\beta}_{\text{Actions}}$ is defined analogously.

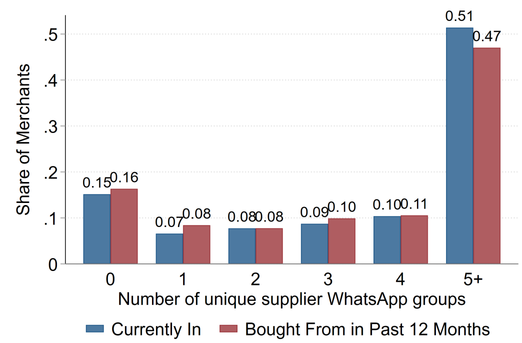
Column 1 is 1 if the firm travelled for business in the past 3 months. Column 2 is 1 if the firm travelled for business to China in the past 3 months. Column 3 is 1 if the firm travelled for business to Turkey in the past 3 months. Column 4 is 1 if the firm travelled for business in the past 3 months. Column 5 is 1 if the firm travelled for business to China in the past 3 months. Column 6 is 1 if the firm travelled for business to Turkey in the past 3 months. Travel is 1 if either the firm owner or someone closely involved with the firm travelled internationally for firm-specific business in the past 3 months.

## Figures

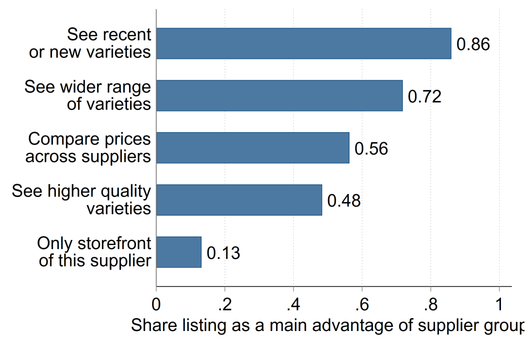
Figure A1: Social Media Usage (Physical Store Only)



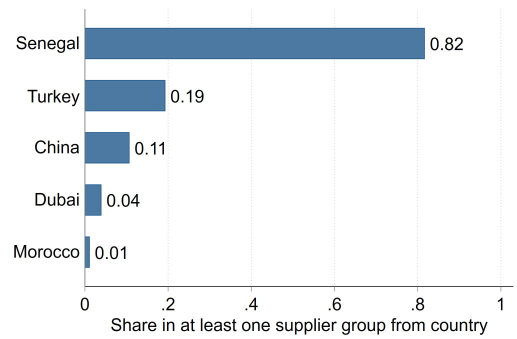

(a) Social Media Usage




(b) Supplier WhatsApp Groups



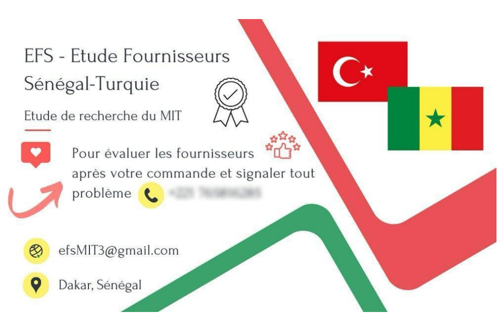

(c) Advantages of Supplier Groups



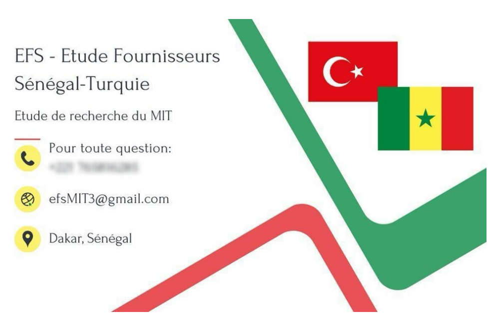

(d) Supplier Groups, by Supplier Origin

*Note*: This figure shows a number of statistics about how firms in our sample use social media to obtain information about suppliers. It is the same as Figure 2, but instead calculates statistics only for the 607 firms that have physical stores. Panel (a) shows the results of a question asking firms to select all social media that they use to obtain information about suppliers for their business. Panel (b) shows the distribution of the number of supplier WhatsApp groups a firm is in at the time of the baseline survey, as well as the distribution of the number of such groups that the firm has directly made at least one purchase from in the past 12 months. Supplier WhatsApp groups are defined as WhatsApp groups in which the primary purpose is for suppliers to advertise their wares to downstream clients. Panel (c) shows the results of a question asking firms that use supplier WhatsApp groups to select all reasons why they find these groups useful. Panel (d) shows the share of firms who are in at least one supplier WhatsApp group where the supplier located and based in the country listed.

Figure A2: Business Cards for Hidden Actions Treatment

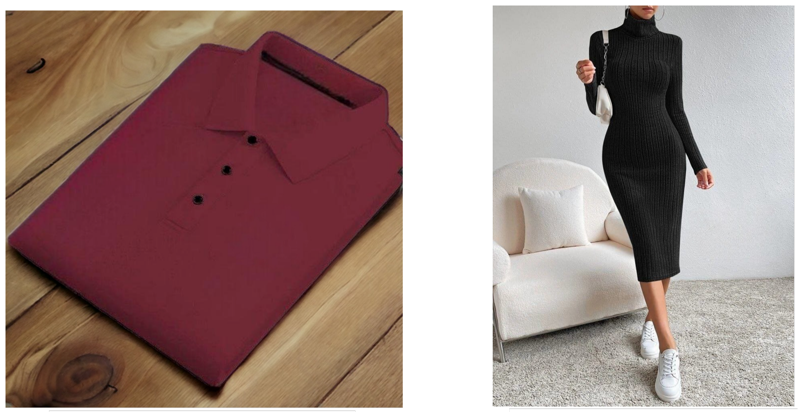



(a) Treatment




(b) Control

Figure A3: Mystery Shopping Goods (Examples)

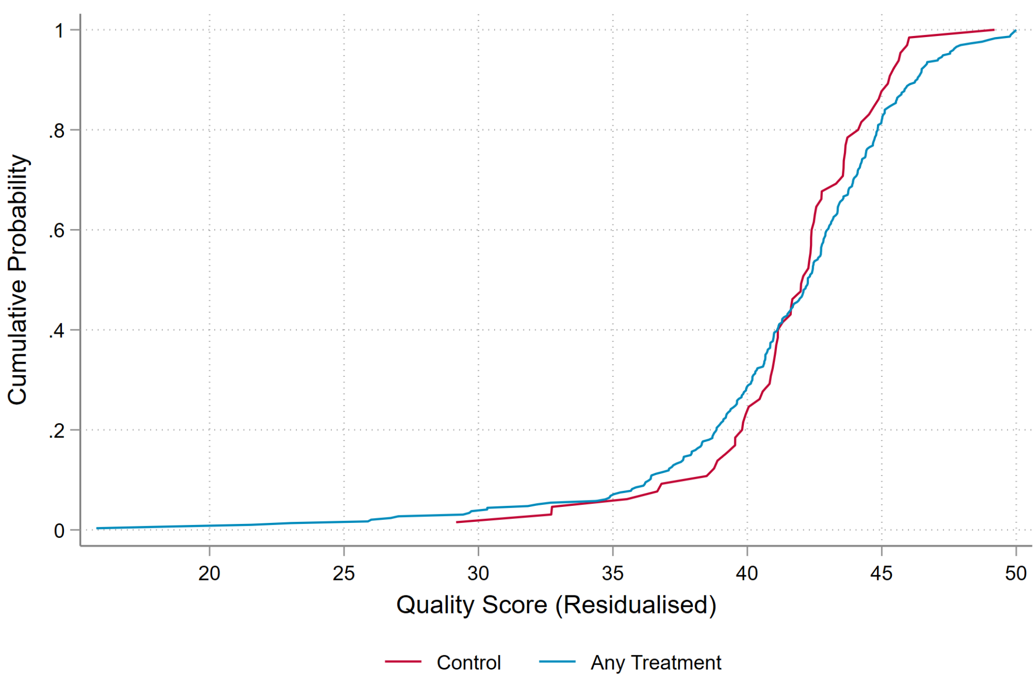


1. *Red*
2. *One colour*
3. *No large logo/print*
4. *3 black buttons*
5. *Size L*

1. *Black*
2. *Long sleeves*
3. *Knee length*
4. *Turtleneck*
5. *Ribbed Cotton*

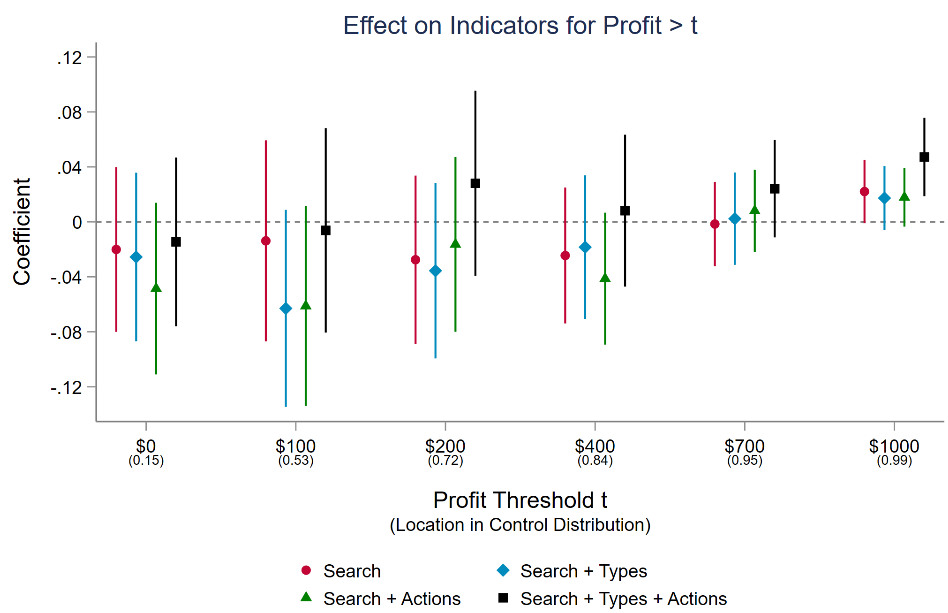
Examples of goods requested in the mystery shopping exercise. In total, there were 28 different goods.

Figure A4: Quality Score Distribution

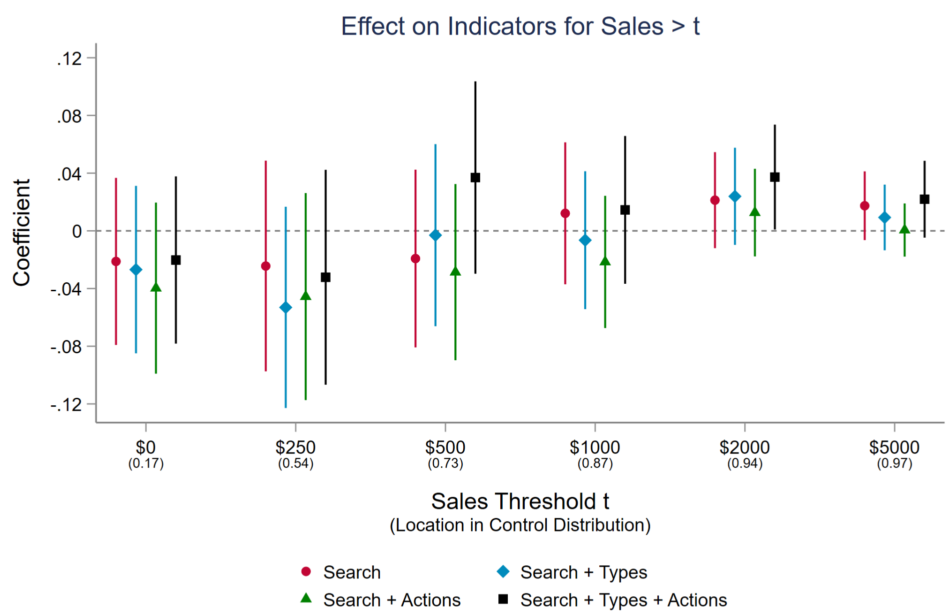



*Note*: This figure shows CDF of the quality score separately by treatment status, with all four treatment groups (Search Only, Search + Types, Search + Actions, Search + Types + Actions) pooled for ease of readability. To be consistent with the regression in the table, we first residualise quality using stratum fixed effects and the covariates selected in the regression.

Figure A5: Threshold Regressions for Profit and Sales



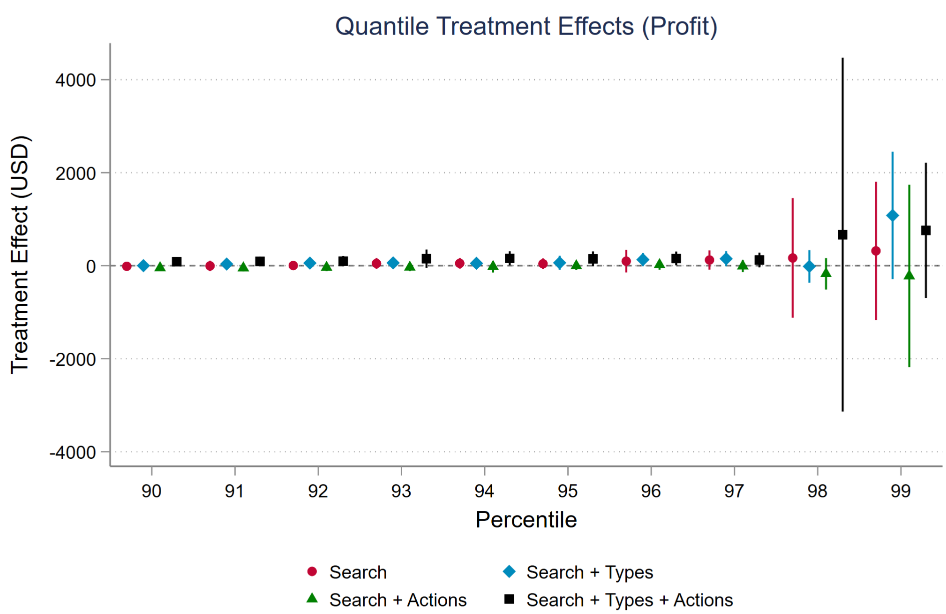

(a) Profit



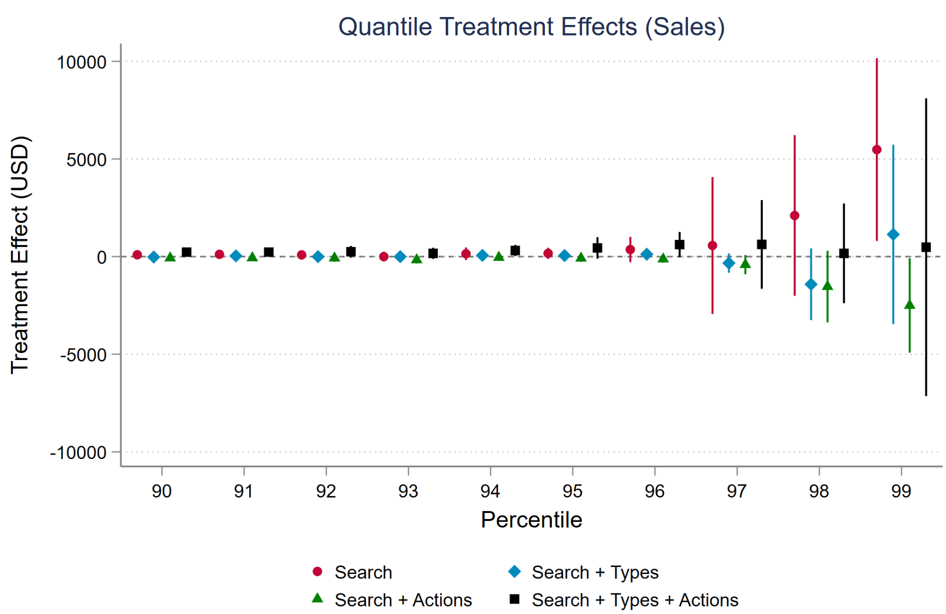

(b) Sales

*Note*: This figure shows the coefficients from regressions of indicators for whether profit and sales are above some threshold $t$, for a range of $t$. All regressions include covariates selected by Double Lasso (Belloni, Chernozhukov, and Hansen, 2014), as well as the outcome measured at baseline (if available). The numbers in parentheses show the percentiles at which $t$ is located in the distribution of the pure control group. We plot 95% confidence intervals constructed using randomisation inference, defined as the set of sharp nulls that do not reject at the 5% level, using the procedure in Young (2024).

Figure A6: Quantile Treatment Effects (90-99)



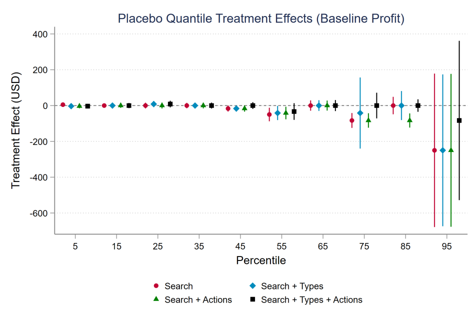

(a) Profit



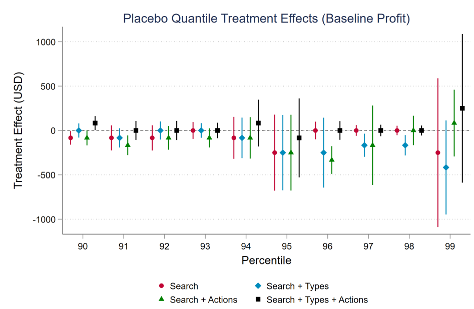

(b) Sales

*Note*: This figure shows the coefficients from quantile regressions of profit and sales on the four treatment groups, for quantiles 90-99. All quantile regressions include the outcome measured at baseline (if available), but otherwise do not include any covariates. We plot 95% confidence intervals constructed using randomisation inference, defined as the set of sharp nulls that do not reject at the 5% level.

Figure A7: Placebo Check: Quantile Treatment Effects on Baseline Profit




(a) Percentiles 5-95




(b) Percentiles 90-99

*Note*: This figure shows the coefficients from quantile regressions of baseline profit on the four treatment groups, intended as a placebo test. As the only covariate included in the main quantile regressions is the outcome measured at baseline, which is itself the outcome here, we do not include any covariates. We plot 95% confidence intervals constructed using randomisation inference, defined as the set of sharp nulls that do not reject at the 5% level.