Does Gender Matter for Small Business Performance? Experimental Evidence from India*

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February 2021

Abstract

Many well-known studies have shown that female-owned micro-enterprises are less profitable and have lower returns to capital than their male-owned counterparts. This raises an important question: what drives the estimated gender gap in business performance? In this paper, we investigate two possible drivers for this gender gap: 1) buyers are less likely to buy from women-owned businesses (demand-side constraints) and/or 2) women business owners use different business practices than men. Using two field experiments, we precisely reject both of these explanations. We examine this question in the context of vegetable sellers in India, a context where observationally women make less than men. We conduct two field experiments that hold every business aspect fixed except for the gender of the owner. More specifically, we set up our own shops so that location, goods supplied, and hours of operation are held constant. In Experiment 1, we identify demand-side constraints by training confederate sellers to sell packaged goods at fixed prices using a standardized script, thereby controlling for seller behavior, such as bargaining styles. In Experiment 2, we only control for business characteristics (e.g. location, goods, hours), letting seller behavior respond endogenously. In both experiments, we find that women earn at least as much as men. Our results indicate that the estimated gender earnings gap in this context is neither due to differential demand-side constraints nor to seller behavior, but instead is likely driven by differences in capital constraints and location.

*We thank our main advisors, Pascaline Dupas and Jesper Sørensen, and our committee members, Marshall Burke, Marcel Fafchamps, John-Paul Ferguson and Aruna Ranganathan, for their support. We also thank our extraordinary field team led by Shashank Sreedharan and Khushboo Gupta for their invaluable data collection efforts, as well as the staff at IFMR-LEAD for their assistance. This project would not have seen the light of day without support from the following funders: Weiss Family Program Fund for Research in Development Economics at Harvard University, Stanford Institute for Economic Policy Research, Stanford Vice Provost for Graduate Education, Stanford School of Humanities and Sciences, Stanford Institute for Innovation in Developing Economies, the Freeman Spogli Institute for International Studies, and Stanford Center for South Asia. The pre-analysis plan for this study was registered on the American Economic Association's registry for randomized controlled trials # AEARCTR-0003180.

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1 Introduction

While the gender gap in wages has been well-documented (Barth, Kerr and Olivetti, 2017; Blau and Kahn, 2017; Goldin et al., 2017), even self-employed women earn less than men (Global Entrepreneurship Monitor, 2012). This is important because self-employment is a very common type of occupation. Close to 50% the working population is self-employed worldwide, and in India for example, this ratio goes up to 75% (World Bank, 2020*a*). The gender gap in business profitability has been reported globally and is substantial: self-employed men make twice as much profit as women in many contexts, including in the United States (Scott and Shu, 2017; Guzman and Kacperczyk, 2019). This gap is particularly relevant in developing economies (De Mel, McKenzie and Woodruff, 2008; Banerjee et al., 2015; Nix, Gamberoni and Heath, 2016; Hardy and Kagy, 2018), where self-employment is often more common than wage employment (World Bank, 2020*b*).

While the causes of this gap are not well understood (Guzman and Kacperczyk, 2019), several factors have emerged as likely explanations. First, women-led firms tend to be concentrated in low-productivity sectors (Cirera and Qasim, 2014). Yet, even when male and female entrepreneurs operate in similar sectors, the gap persists (Hardy and Kagy, 2018). More specifically, well-known studies have shown that the returns to capital for micro-enterprises are substantial for male-owned enterprises – but zero for their female counterparts (De Mel, McKenzie and Woodruff, 2008, 2009*b*; Fafchamps et al., 2014; Berge, Bjorvatn and Tungodden, 2015). All these factors raise an important question: what drives this estimated gender gap in business performance?

This paper studies the gender profit gap among vegetable sellers in India. Our survey data shows that the gap is large: female sellers make 50% less than their male counterparts. We are going to look at two main hypotheses that could explain why women might be earning less using two field experiments. First, we will test whether buyers are less likely to buy from women than men. In other words, on the extensive margin, do women sellers receive less customers? Observationally, our survey consumer data show that, conditional on visiting a vegetable shop, the average buyer in the markets where our sellers operate is more likely to buy from a male than a female seller, but gender is correlated with business characteristics. Second, we will test whether women use different business practices than men. On the intensive margin, is the experience of a customer different in a man-owned vs. woman-owned business? Observationally, our survey evidence also shows that women have much lower inventory, 40% less than men. But in which way does the causality run? For example, do buyers' preferences for male sellers limit the scale at which female sellers can operate? Do male and female sellers bargain differently with buyers, and do female sellers lose buyers in the bargaining process? Are women constrained in their entrepreneurial ability? Or do the different sellers' business characteristics, such as inventory or location reduce the appeal of their business? Our survey data additionally suggests a number of different explanations for the gender gap in profitability, such as differential access to credit, or selection. For example, women are have significantly lower levels of education and are more likely to come from disadvantaged castes. These hypotheses are *not* the focus of this paper.

To test our two hypotheses, we conduct two field experiments among market vendors in India to identify the role of each class of constraints (Bertrand and Duflo, 2017). In the first experiment, we test whether customers are less likely to buy from a female compared to a male entrepreneur. To do so, we control for all supply-side characteristics and seller behavior (using a bargaining script), enabling us to identify the effect of demand-side constraints on the gender profit gap. We therefore get an estimate of the combined effect of consumer and seller behavior on business performance. In our second experiment, we allow for seller behavior to be endogenous and only control for supply-side characteristics. Sellers can use bargaining techniques and interact or negotiate with customers as they wish. Comparing the results from both experiments thus allows us to determine the effect of seller behavior on business performance and to test whether this varies by gender.

In the first experiment, we set up two market stalls and supply them with goods identical in type, quantity, and quality. We hire confederate sellers to work in our stalls, keeping hours worked, location, size, and setup constant. Every day, we randomly assign one male and one female seller to each of our two shops, thus exogenously varying the seller's gender. In addition, we experimentally keep seller behavior constant by training the confederate sellers to interact with customers in the same manner and by requiring them to sell at fixed prices, using a bargaining script. Since we control for all business characteristics and seller behavior, this experimental design allows us to identify demand-side constraints affecting the gender profit gap. We find that when men and women operate the same business and interact with customers in the same way, their profits are identical. This result is precisely estimated, and if anything, our results are suggestive that women make slightly more, though the difference is small in magnitude and not statistically significant. This shows that demand-side constraints do not constitute a barrier to the profitability of female-owned micro-enterprises in this context.[1]

Having identified the impact of demand-side constraints on the gender profit gap, our next step is to determine the role of seller behavior. To that end, our second experiment relaxes the constraint that sellers behave in the same way. Similar to our first experiment, we set up market stalls and supply them with identical goods. However, we no longer train sellers to use a bargaining script. Instead, we allow sellers to bargain, negotiate, price, and interact with buyers as they see fit. For that reason, we recruit experienced vegetable sellers instead of confederate sellers. In this experiment, we only control for the business characteristics by keeping hours worked, location, size, and setup constant. By comparing the results from both experiments, we can identify the effect of seller behavior on the gender profit gap. Once again, we find no difference in performance between male and female sellers, which suggests that seller behavior does not limit female micro-entrepreneurs. Additionally, we find no difference in bargaining or pricing between male and female sellers.

Together, these results suggest no role for demand-side constraints or seller behavior

[1]Our experiment looks at sellers who offer fixed prices. Theoretically, it is still possible that demand-side constraints exist in this context, but only manifests when men and women do not bargain in exactly the same way (so behavior across genders is fixed). E.g., it could be that customers like bargaining with women less than bargaining with men. Our next experiment will help rule out this possibility.

in explaining the gender profit gap after the business has been set up. They also suggest a limited role for selection into the vending profession, since female sellers in Experiment 2 perform as well as male sellers, despite coming from more disadvantaged backgrounds.[2] Gender differences in profits must therefore come from factors that affect business inputs – the quantity and quality of goods sold, location, or hours worked. Thus, providing male and female sellers with equal inputs and location closes the gender profit gap. In our baseline survey, we document that indeed there are substantial gender differences in inventory, but that men and women work the same hours. Further work is needed to document the extent of gender differences in location and access to capital. Our results suggest that one potential policy for reducing gender profit gaps should aim at equalizing access to upstream suppliers.

Our findings contribute to the literature on resource constraints for micro-enterprises in developing countries (Jayachandran, 2020). The seminal experimental studies by De Mel, McKenzie and Woodruff (2008, 2009*b*) estimate returns to capital for micro-enterprises in Sri Lanka by providing large capital grants to a random set of business owners. While they estimate substantial positive returns to capital for male-owned businesses, they find zero returns to capital for their female-owned counterparts. Similarly, Fafchamps et al. (2014) find zero returns to capital among female-owned enterprises that are small in size. However, for larger female-run businesses, they find positive returns when capital is given in kind, but zero when it is in cash. For male-owned businesses, they estimate positive returns to capital, regardless of whether the grant is cash or in kind. The persistent gender gap in estimated returns to capital constitutes a puzzle, for which a recent paper by Bernhardt et al. (2019) offers a new explanation. This paper revisits the experimental studies by De Mel, McKenzie and Woodruff (2008) and Fafchamps et al. (2014). The authors show that when the capital grant recipient is a woman, on average household income increases. They argue that the lack of effect on profits among female-owned enterprises is because women's capital tends

[2] While this is not the focus of our paper, this point suggests either the returns to an "advantaged" background —education, connections, work experience—are not high, or that women perform better conditional on "advantage."

to be invested into their husband's business. This important finding suggests that returns to capital among female-run enterprises might not be zero as previously estimated. Our paper is in line with this result. Since we provide men and women with identical businesses, our experiment can be viewed as an extreme capital drop intervention – in particular, one where capital cannot be diverted to a spouse's business. Since we find no profit differences between male- and female-run businesses after equalizing all business characteristics, our results suggest that returns to capital may not differ between men and women.An alternative explanation is that women benefitted more from our treatment, since after equalizing business characteristics, the gender gap disappears.

Beyond contributing to the literature on supply-side constraints for female-run micro-enterprises, our paper is part of a growing literature that examines whether demand-side barriers are a barrier for female entrepreneurs. Previous studies of gender dynamics in marketplaces have suggested that female sellers face a penalty from buyers. List (2004) shows that in the sportscard market buyers give lower initial and final offers to female sellers than to male sellers. Through bargaining, female sellers are able to reduce some of the discrepancy; however, the final offer is still significantly less than that of white males. Kricheli-Katz and Regev (2016) compare transactions of identical goods sold online by male and female sellers and shows that female sellers receive significantly less than male sellers who sell identical goods. In Ghana, Hardy and Kagy (2020) experimentally vary demand shocks to small firms in the garment sector and observe how firms respond to these shocks. While male-owned firms have to displace their current production to accommodate the demand shocks, female-owned firms are able to meet the demand right away. This suggests that female-run firms face a lower demand than male-run firms. Taken together, these studies suggest that buyers are less willing to purchase goods from female-run businesses. Our first experiment directly tests this hypothesis in a real-world market for non-gendered goods. Unlike previous studies, we find no evidence that the demand for goods sold by women is any different from the demand for goods sold by men.

This paper also contributes to the behavioral literature on gender differences in bargaining and negotiating. Recent research shows that women are more reluctant to enter negotiations and, when they do, they are less successful than men (Exley, Niederle and Vesterlund, 2018). While the majority of these papers rely on evidence from lab experiments, few studies provide evidence from real-world interactions between buyers and sellers. Castillo et al. (2013) examines gender differences in bargaining in the taxi market in Lima, Peru. After training male and female passengers to negotiate in the same way, male passengers face higher initial prices, final prices and rejection rates from drivers than female passengers. Fitzpatrick (2017) also finds gender differences in the anti-malarial drug market. Female buyers are presented with higher initial prices, but are more successful at bargaining than male buyers, which leads them to obtain the same final price as male buyers. These papers present evidence that sellers bargain differently depending on the client's gender. Our study is one of the first to examine how the gender of the seller (as opposed to the buyer) affects bargaining and negotiations. By collecting a unique transaction-level dataset, we find that male and female sellers price and bargain in the same way.

Our results are especially relevant when considering the fact that poverty disproportionately affects women. To address this problem, a pragmatic response would be to identify ways to increase women's earnings to alleviate their poverty. Doing this can lead to many positive outcomes, such as improved health and nutrition for children, increased investments in children's education, and lower fertility (Duflo, 2012). While direct cash transfers to women are an effective way to achieve such positive outcomes (Baird et al., 2013), another way to increase women's earnings is to raise the income of women who work, for example by bridging the gender gap in profitability.

In what follows, we provide a brief overview of vegetable markets in India in Section 2. In Section 3, we detail our experimental design, before presenting results from both experiments in Section 4. In Section 5, we discuss our results. Finally, section 6 concludes.

2 Vegetable Markets in Jaipur

2.1 Setting

We study vegetable markets in Jaipur, India. Jaipur is a medium-sized city in India with roughly 3 million inhabitants. It is the capital and the largest city of the state of Rajasthan, located in the North of the country. India represents close to a fifth the world's population.

In India, micro-enterprises in the informal sector are the most common type of female-owned businesses, comprising some 3 million businesses (World Bank, 2014). An estimated 5-10 million people in India earn a living from selling vegetables, and "India's supermarkets account for only 2% of food and grocery sales" (The Economist, 2014).

We chose to study vegetable markets not only because they an important part of India's informal economy, but also because they are a gender-neutral sector. Since our focus is on the profit gap between male and female micro-entrepreneurs who operate in the same sector, it was crucial to identify a type of market that sellers and buyers of all genders participate in.[3] Our data shows that among all the vegetable markets in the city of Jaipur, 25% of sellers are women, which is consistent with India's 27% female labor participation rate (World Bank, 2018).[4] Thus, vegetable markets are a sector where it is not counter-normative for men or women to operate a business. In addition, 61% of the buyers in these markets are men. Moreover, vegetables are goods that are not inherently gendered (unlike, for example, clothing), and male and female sellers do not generally specialize in different vegetables.[5] We specifically chose this setting so that any differential demand between male- and female-run

[3]For this reason, when we were exploring which setting to conduct our study in, we decided against fruit markets, because there were no female-owned micro-businesses selling fruits. It is worth noting that in other parts of the world, such as Sub-Saharan Africa, vegetable vending is a predominantly female occupation; however, that is not the case in our context.

[4]Prior to the start of our study, we visited all vegetable markets in Jaipur and counted the number of men and women selling in each market during peak market times.

[5]One exception is potatoes and onions, which some male sellers specialize in. However, it is not uncommon for women to sell potatoes and onions in smaller quantities along with other vegetables.

businesses cannot be attributed to the types of goods sold.[6]

Vegetable sellers are small business owners and selling vegetables is typically their only economic activity. Every day, they purchase vegetables at the city's wholesale market early in the morning, and then spend the rest of the day selling the produce at their shops. These shops are small stalls in various vegetable markets dispersed throughout the city, and constitute the main source of produce for the city's inhabitants. Sellers typically work 10 hours at their stalls, 7 days a week.

A key feature of these markets is that they are extremely competitive. The large number of sellers in these markets makes it unlikely that any one of them can reasonably influence the market price. In terms of the logistics for this experiment, we also wanted a sector with low search costs so that buyers could easily switch seller if they wanted to. This allowed us to observe bias in purchasing behavior. These markets are very centralized, and buyers have plenty of outside options if they are not satisfied with any one seller. Buyers shop around by gathering quotes from multiple sellers to compare prices; our data shows that more than 99% of buyers do not buy from a single regular seller. This competitive aspect of the setting also means that established relationships between buyers and sellers are not the norm.

Furthermore, male and female sellers do not produce the items that they sell, since business owners buy produce from the wholesale market daily and resell to individual customers.[7] This implies that there is limited variation in the quality and type of products across sellers. The main price variation occurs from day to day based on the supply of produce at the wholesale market.[8]

Though there are no posted prices, buyers and sellers can gather price information at

[6]Unlike our paper, Hardy and Kagy (2020) studies the garment sector, which is inherently gendered, and find evidence that female-run businesses have lower demand. List (2004) shows that buyers discriminate against female sellers in the market for sportscards, which is largely dominated by men.

[7]There is one large wholesale market, just outside of the city, from which the vast majority of sellers purchase their produce in the morning. If they do not purchase from this wholesale market, sellers buy their stock from another smaller wholesale market in the city. There are therefore only two wholesale markets from which all sellers supply their shops.

[8]This evidence was gathered from multiple qualitative interviews with vegetable traders at the wholesale market. Similar narratives emerged across all respondents interviewed.

minimal cost by asking any seller. Interactions in these markets are brisk; they tend to be fast-paced, short, and without chit-chat. In our setting, the business owner is the only one who is both making decisions about the transactions and also directly interacting with customers. An advantageous feature of this setting is that it allows us not only to observe the realized transactions but also to see the search behavior of buyers and the seller's behavior. To gain more context about the ways in which interactions unfold at the market, our research assistant transcribed the content of all interactions between sellers and buyers for a few days at different shops. The content of a typical interaction occurs as follows:

Buyer: How much is okra? I want 1 kg.

Seller: 60 per kg.

Buyer: I'll take it.

While typically very short, the seller occasionally calls back the buyer if the latter leaves. Buyers also sometimes try to bargain with the seller, though that is not systematic. All of these features make vegetable markets a sector one where we do not expect the type of goods sold or the gender composition of buyers and sellers to put neither men nor women at a disadvantage. This choice was deliberate, since our focus is on demand-side constraints that may exist even in sectors that are not *a priori* unfavorable to women.

Although the type of goods sold in vegetable markets and their gender composition should not put women at a disadvantage, demand-side constraints could still matter. First, a growing body of literature presents evidence that female sellers face lower demand for their goods, even when the goods they sell are gender-neutral (see, for example Kricheli-Katz and Regev, 2016) for differences between male and female sellers of Amazon gift cards). Second, our setting is one with high gender inequality, which could lead to discrimination towards female sellers. Rajasthan is a conservative state with severe gender inequality and one of India's states with the most severe sex ratio (Duflo, 2012).[9] In developing countries, gender disparities tend to be larger across all dimensions than in developed countries (Jayachandran, 2015). India, where our study takes place, is a striking example in terms of under-representation of women in the labor force. There, the likelihood to be working is three times lower for women compared to men (World Bank, 2018). In the north, where our study site of Jaipur is located, gender inequality is even starker compared to the south (Dyson and Moore, 1983). We could therefore expect to observe gender differences in buyers' behavior in terms of search and purchase.

2.2 Characteristics of Vegetable Sellers and Buyers

2.2.1 Sampling Frame

The first phase of data collection started in July 2017 (see Figure A2 for a complete timeline) and the last phase ended in February 2019.

In the first phase, we looked for a suitable setting to study our research question and chose vegetable markets in Jaipur, India. We first conducted qualitative work in these markets, observing interactions and collecting some basic information by interviewing buyers and sellers. We also visited the wholesale market to understand the supply chain of products. We designed a survey instrument and surveyed a representative sample of 101 sellers. In the first phase, we also ran a version of our experiment with an initial sample of 38 sellers. In the second phase, we did more qualitative work and conducted a survey of buyers. Finally, in the third and last phase, we created a sampling frame of 1,112 sellers, from which we surveyed a representative sample of 237 sellers, and ran our two field experiments. This extensive fieldwork allowed us to collect fine-grained data to understand the patterns at play in this setting.

[9] Sex ratio is the proportion of males to females in a given population. The natural sex ratio is extremely close to 1:1. Gender imbalance is generally used an indication of the existence of sex-selective abortions. Parents might have a stronger preference for boys, since boys are expected to contribute to the family more than girls. Even before birth, such beliefs can lead to sex-selective abortions, causing an estimated half a million "missing" girls in India alone between 1995 and 2005 (Bhalotra and Cochrane, 2010).

Our sampling frame consists of all vegetable sellers from all large markets in Jaipur, where we define a market as large if 30 or more sellers regularly work there. We chose to focus on large markets for three reasons. First, since our experiment involves introducing new sellers to a market, the large number of sellers ensures that our experiment is unlikely to influence the market price or create extra competition for current sellers. Second, in large markets, buyers shop around more and are less likely to have established relationships with sellers, unlike in smaller neighborhood markets where such relationships are more prevalent. Thus, the sellers in our experiment do not look out of place and can still attract new clients. Finally, all markets with more than 30 sellers had at least 5 female sellers, which was our second criteria. This ensures that the new female seller who enters the market as part of our experiment does not stand out because of her gender. There were 14 markets that met our criteria; after keeping one for piloting survey instruments, we were left with 13 markets scattered throughout the city (see Figure A3 for a map of these markets).

To create the sampling frame, our team of surveyors collected basic information about every owner located in the selected vegetable markets, including the seller's gender, age, education, and experience, as well as number of employees. This listing survey was used to both identify businesses that fit our sample criteria and to generate a benchmark for our final sample by controlling for variables besides gender. We listed 1,112 sellers in 13 markets.

2.2.2 Characteristics of Vegetable Sellers

After finishing the listing survey, we conducted a baseline survey with a subset of the identified firms. We randomly selected 237 business owners that consented to be part of our study. The goal of our baseline survey was twofold. First, we wanted to have a real-world measure of the gender profit gap in this setting. Second, we wanted to measure the baseline performance of sellers in their own stalls before they took part in our experiment. For each participant, we assigned a surveyor to collect data about individual and business characteristics. The surveyor would then sit with the seller for multiple hours of their work day, recording information for every transaction, such as quantity sold, price paid, type of vegetables sold, buyer's gender, and some bargaining data.

We first present descriptive statistics about the female and male small-business owners in our representative sample. Table 1 describes the individual characteristics of sellers in our sample. We first observe that men and women are very similar in terms age and experience. However, women in our sample are significantly less educated than men. On average, they completed 1.16 years of education, versus 7.23 for men, a disparity that is statistically significant and somewhat larger than the national average in India.[10] In terms of caste, men are more likely to come from the general caste, which is considered upper-caste (25% of men versus 2% of women). Women are also more likely to come from the "Scheduled Caste," the official term used by the Government of India for the lowest castes (45% of women versus 27% of men). The vast majority of sellers are Hindus, though 16% of men are Muslims. These gender differences in caste and religion are statistically significant at the 1% level. Taken together, the disparities in education and caste highlight an important fact: female sellers disproportionately come from disadvantaged backgrounds.

[Table 1 about here.]

We document a substantial gender gap in earnings among our survey sample. As can be seen on Figure 1, female business owners earn less than male business owners. This figure depicts the kernel density function of self-reported daily revenues in rupees for men and women. Among these business owners, men report earning roughly 50% more than women in terms of daily revenues, a difference that is statistically significant at the 1% level (Table 2). Since such self-reports might be inaccurate, we compare them to second measure. For a subset of our sample, our surveyors asked business owners about their cash holdings at the beginning and at the end of their visit. Through a simple subtraction, we confirmed the estimate that men earn roughly 50% more than women (Table 2). All our measures

[10] As of 2017, the national average for India is 4.8 years of schooling for women, and 8.2 for men (UNDP, 2017).

of revenues go in the same direction, showing that female business owners report earning significantly less than men. We find the same patterns whether we look at our representative sample of business owners, or at the participants in our experiment only.

[Figure 1 about here.]

[Table 2 about here.]

To better understand how a business owner's gender interacts with business characteristics and profitability, we use a linear regression model in Table 3. This regression allows us to explore the patterns of correlation in our observational data. As expected, being male is associated with much higher earnings. We first look at the unconditional effect of being male on business profitability. In model (1), we look at the relationship between daily revenue in rupees and the dichotomous variable indicating that the seller is male. We find a positive and significant effect of being male on profitability. The magnitude of this effect is large, since being male is associated with an increase in profits of Rs 1,544 ($p<0.01$). As we control for the value of inventory in model (2), the effect of being male decreases but remains significant ($p<0.01$). Being male is still significantly associated with an increase in revenues once we control for individual characteristics in model (3), such as the business owner's age, years of experience, years of education, caste, and religion, and when we additionally control for market fixed effects in model (4). Interestingly, the other individual characteristics besides gender have a smaller effect than gender, and these effects are not significant. Thus, using different specifications in our regression analysis, we find that being male is strongly associated with higher revenues.

[Table 3 about here.]

In line with the literature on the gender gap in earnings, men's businesses in our representative sample are bigger and generate more revenue. Indeed, our observational data shows that men's inventory is 40% larger than women's ($p<0.01$, Table 4). We use two different measures of inventory; both yield similar results. The first measure is the total amount of inventory at the beginning of the day, valued at the price of purchase at the wholesale market in rupees. The second, the daily cost of all vegetables in rupees, is the business owner's answer when we ask them how much they spent at the wholesale market that morning. We also asked the business owners to report their hours worked on that day. While we see a gender gap in revenues, we do not see a difference in terms of hours worked between men and women (Table 4).

[Table 4 about here.]

2.2.3 Buyer Behavior Towards Male and Female Sellers

In addition to collecting data on sellers, we conducted a survey of buyers to understand their purchasing habits and motivations. This survey was carried out in five of the thirteen markets in our sample, and buyers were randomly selected to participate. In total, we surveyed 52 female and 61 male buyers. In this survey, we first asked buyers questions about their age, household composition, education, perception of male and female sellers, as well as habits regarding the purchase of vegetables. We then followed buyers with their consent as they went about the market to purchase vegetables. We captured fine-grained data on their search and purchase behavior, including number of stalls visited, quotes, bargaining attempts and actual purchases. We recorded information on every stall where buyers made an inquiry about a price and/or made a purchase. Conditional on visiting a stall, buyers were more likely to buy if the seller was a man (Table 5, $p<0.05$). Thus, our survey data suggests differential buyers' behavior based on the seller's gender in this context. However, we cannot immediately attribute such differences to gendered differences in business characteristics (e.g., male sellers have larger stalls), differences in buyer/seller interactions (e.g., male sellers are better at marketing their goods and at bargaining), or differential buyer demand based on the seller's gender (e.g, buyer discrimination).

[Table 5 about here.]

Our observational study confirmed what was already evident in the literature: men earn more, but many other determinants could operate. Buyers are more likely to purchase from a shop if the seller is male, conditional on visiting a shop. However, large differences in inventory between male and female business owners suggest that we do not yet know whether the differential buyers' behavior by gender is due to one or the other, or to gender differences in buyer-seller interactions. It is unclear whether men and women could earn the same with the same businesses. Thus we specifically designed two experiments to successively control for all supply-side characteristics and seller behavior. This allows us to first identify demand-side determinants, and then examine the role of seller behavior. We designed our experiments based on findings from our observational surveys of buyers and sellers.

3 Experimental Design

3.1 Overview

Our observational data shows patterns congruent with the literature: women earn less but own smaller businesses. Buyers might therefore prefer to buy from men based on different preferences for a seller's gender, or based on gendered differences in business characteristics. It is also possible that buyers prefer to buy from male sellers if the latter price and bargain differently. The goal of our experiments is to test the extent to which buyers' and sellers' behavior differentially affect male and female business owners' revenues and profits, as opposed to gendered business characteristics. We ran two field experiments to break the relationship between owner's gender and business characteristics. In both experiments, we controlled for all supply-side characteristics. We did so by setting up our own market stalls and supplying them with goods that were identical in type, quality and quantity. We recruited male and female sellers to work in our stalls, and randomly assigned one male and one female seller to each shop. Moreover, male and female sellers worked the exact same hours. Goods were covered until the beginning of the experiment, and all shops were closed precisely at the same time. Thus, in both experiments, we hold business characteristics and inputs constant and randomly vary the seller. In Experiment 1, we identify demand-side constraints by additionally holding sellers' behavior constant. We did so by training confederate sellers to sell packaged goods using a script. In Experiment 2, we relax the constraint on sellers' behavior by recruiting experienced vegetable sellers and allowing them to interact and bargain with buyers as they wished. Thus, in Experiment 1, we control for supply-side characteristics and seller behavior, whereas in Experiment 2 we only keep supply-side characteristics constant across gender. An overview of our experimental design and the variables held constant in each experiment can be seen in Table 6.

[Table 6 about here.]

3.2 Experiment 1: Isolating demand-side constraints

In our first experiment, we set up our own market stalls and bought inventory, effectively starting our own businesses. We recruited college students and surveyors to act as confederate sellers, and trained them to interact with sellers in a scripted way. Thus, any differences in performance between male- and female-run shops can be attributed to buyer behavior.

To completely rule out potential differences in perceived quality, we chose to sell packaged goods that do not vary in quality (biscuits, savory snacks and fruit cake). This is important if buyers believe that quality is correlated with the seller's gender. By selling packaged goods, we controlled buyers' perceptions of quality – since quality was held constant.[11] These goods are well-known branded goods, manufactured and packaged by a third-party company. Packaged goods are typically sold in shops, not in markets. This has multiple advantages. First, since our stalls were innovative, it is unlikely buyers would have made inferences based on a seller's gender. In addition, since there were no other nearby shops

[11] As it was, using packaged goods with constant quality turned out to be less important than we expected, since we do not find a difference in buyers' behavior in Experiment 2 using vegetables, for which quality and perceptions of quality might matter more. However, we chose to include this type of goods in our experiment at the time of pre-registering the study, because we thought that buyers might perceive the quality of goods differently based on the seller's gender.

selling similar packaged goods, our two shops constituted the entire market for these goods. This allows us to directly test which of the two shops buyers preferred. Finally, the fact that we started selling goods right away indicates that there is a demand for this type of goods. We also selected goods that are not gendered – both men and women might want to purchase them.

We set up two stalls in a large vegetable market and supplied each stall with the same type and quantity of packaged goods. We recruited and trained 14 male and 19 female college students, and 6 male and 5 female surveyors to act as confederate sellers. We randomly assigned one male and one female confederate seller to one of our two stalls every day. Most confederate sellers participated more than once, for a total of 122 seller-days. These sellers were trained to behave in a scripted way. In particular, they were instructed not to do any bargaining or vocal marketing. Confederate sellers were paid a fixed wage to ensure they complied with instructions and put no extra effort in selling. Additionally, surveyors collecting data sat next to them and monitored their behavior. By relying on trained confederates to sell in the same way, we remove by choice any gender differences in bargaining.

We also controlled the selling price, since sellers were instructed to sell at the Maximum Retail Price (MRP), which is typical for packaged goods in India. Since prices are fixed in this experiment, any difference in performance is due to differences in number of sales and quantity sold. In addition, surveyors were trained to set up stalls to make them look identical, using the same tools (e.g, cash boxes, baskets). A picture of our two stalls for this experiment can be seen in Figure 2. Surveyors also ensured that, on a given day, all shops opened and closed at the exact same time, so that all sellers worked the same hours. In this experiment, we hold all supply-side characteristics constant, including business characteristics, prices and seller behavior. This design allows us to attribute any gender differences in performance to discrimination by buyers.

[Figure 2 about here.]

3.3 Experiment 2: Isolating the effect of seller behavior

Our second experiment is similar to our first, but differs in three ways. First, the goods sold were vegetables, and not packaged goods. Second, we recruited experienced vegetable sellers instead of surveyors and college students. Third, we allowed sellers to price and bargain as they wished; we no longer controlled for seller behavior. Since only business characteristics are held constant, any difference in profits can be attributed to differential buyers' or sellers' behavior. Experiment 2 serves two purposes. First, it constitutes a test for buyer discrimination in a more natural setting, where the goods sold are ubiquitous and sellers are allowed to interact with buyers in a natural way. Second, it allows us to observe and quantify any gender differences in seller behavior, with a specific focus on pricing and bargaining.

To set up our own vegetable shops, we reached an agreement with the market leaders, who authorized us to set up our stalls in the same location every day. Over the span of five months, we operated six stalls in three markets, always in pairs, where one was staffed by a man and one was staffed by a woman.

Every day, we bought hundreds of pounds of vegetables from the wholesale market to stock our pairs of stalls with produce that was identical in type, quantity, and quality. We supplied vegetables commonly sold by both men and women, based on our observational survey: tomatoes and one of okra, peas, or cucumbers, depending on the season. On a typical day, we provided sellers with around 40 kg ($\sim$ 88 lbs) of tomatoes, and around 20 kg ($\sim$ 44 lbs) of okra, peas or cucumbers.

To staff our stalls in each market, we recruited 272 experienced vegetable sellers, 136 men and 136 women. We restricted our sample to business owners, as opposed to employees. We defined business owners as people who make all the main decisions concerning the business (quantity, type of items, selling price, borrowing for the business, use of earned money). We asked every business owner these questions to ensure that they actually owned the business.

Since we let sellers behave spontaneously, we had to recruit experienced sellers. We recruited sellers from other markets, in order to avoid pre-existing relationships between sellers and buyers. No seller had previously worked in the market we assigned them to for the experiment. We also wanted to recruit a sample of sellers representative of vegetable sellers in Jaipur and to be able to control for differences among them. It is important to note that in these markets it is not unusual to see a new seller, since sellers sometimes sell in different markets on different days. Additionally, recruiting different types of sellers in Experiments 1 and 2 (surveyors, college students, experienced vegetable sellers) increases the external validity of our results.

We then randomly selected sellers from our representative sample to "own" our vegetable stalls for an entire work day. Within each market, we randomly assigned one man and one woman to sell in each stall every day. To incentivize sellers, we let them keep the daily profits, and sellers did not have to pay us for unsold vegetables.[12] In addition to the profits, sellers were paid a Rs 500 participation fee. We determined the amount of this participation fee in the first phase of our data collection through an experimental game, as we explain in more detail in Appendix A.

Similar to Experiment 1, the setup across stalls was identical, as can be seen in the pictures of our stalls (Figure 3). Goods were covered until the beginning of the experiment, to ensure that the hours worked were exactly the same across sellers. Random assignment of male-female pairs of sellers to location pairs ensures that location, on average, does not affect any performance difference between men and women. Thus, in this experiment, we only controlled for supply-side characteristics (capital, location, hours worked) and allowed buyers and sellers to transact as they wished.

[Figure 3 about here.]

[12] We charged sellers the rate from the wholesale market minus a small subsidy. The subsidy ensured that our rate was competitive.

3.4 Data

For both experiments, one surveyor sat with one seller for the duration of the experiment to record transaction-level data. Each surveyor was assigned to survey one gender-matched seller each day. Our surveyors sat with sellers for the entire duration of the experiment, and recorded details on every transaction, whether successful or not. That is, we captured every instance in which a buyer asked the seller about the price of a vegetable.[13] For every such interaction, our surveyors recorded the gender of the buyer, the price quoted by the seller, whether the buyer attempted to bargain, and what goods were sold at what price, if a sale was made. We also collected data about the business owners themselves. Furthermore, we directly measured revenue by counting cash at the end of the experiment. To ensure that sellers did not bring any funds of their own to use as change, sellers were given Rs 100 in cash at the beginning of the experiment, an amount which we subtracted from our cash count at the end of the day. Thus, our measure of revenue is extremely precise and directly estimated.

3.4.1 Experiment 1

Our main outcome variables for Experiment 1 are revenue and the number of goods sold. We cannot compute profits in this setting because we did not charge sellers for the cost of the goods sold. This was to ensure sellers had no incentive to over-market their goods and interacted with potential buyers in the same way. Furthermore, we purchased and sold the packaged goods at the Maximum Retail Price (MRP), so our profits for each sale were zero. Real sellers of packaged goods typically buy in bulk from wholesalers at a discount and sell at the MRP; however, the quantities we purchased were too small for us to obtain similar discounts. Since Experiment 1 is designed to test for buyer behavior and prices are fixed, revenue and number of goods sold are more meaningful measures of customer demand than

[13] Based on our observations and recordings of interactions between buyers and sellers during the first and second phases of the project, the vast majority of transactions start with the buyer asking the seller for a price.

profits.

3.4.2 Experiment 2

Unlike Experiment 1, our main outcome measure for Experiment 2 is profit. Profits are measured very precisely by directly measuring revenue, as in Experiment 1, and subtracting the cost of vegetables sold. To determine the amount of vegetables sold by each participant during the experiment, we weighed the vegetables that were present in the stall at the beginning and at the end of the experiment. Weighing the vegetables right before the start of the experiment ensured that the exact same quantities were given to each seller. At the end of the experiment, we weighed how much produce was leftover, and separately measured the amount of spoiled produce. This enabled us to measure how much produce each seller had sold. Since we set the costs of the vegetables (we charged sellers the market rate minus a small subsidy), we deducted the cost of vegetables sold from the revenue each seller had made and sellers kept the profits. Each participant was informed of the costs that would be charged prior to the start of the experiment. Additionally, we did not charge sellers for unsold or spoiled produce. Our main outcome variables are daily profit and revenue, but we also use additional measures of performance, such as the number of attempted and completed transactions, markup per rupee, and total quantity sold.

Although we did not charge sellers for spoilage and transport, we argue that the profit margins on each vegetable are realistic, because the costs were based on market prices, and the owners chose at what price to sell. In addition, our measure of the profit gap is rigorous, since our measure of profits is the same across gender and not subject to biases in self-reported revenues and costs.

4 Results

4.1 Experiment 1 Results: demand-side constraints

Figure 4 shows the distribution of revenues for our 122 confederate sellers-days, by gender. As can be seen in Figure 4, women made more on average than men.

[Figure 4 about here.]

Female sellers earned on average Rs 97.50 in revenue, against Rs 63.33 for male (p=0.16) (Table 7). P-values are computed using standard errors clustered at the seller level. Gender differences in revenues and goods sold are robust to trimming the sample at the top and bottom 1% level. Although not statistically significant, these differences suggest that women performed at least as well as men. Recall that in this field experiment, we held constant the seller's behavior using a bargaining script, so this (insignificant) difference can not be due to gender differences in behavior, ability, or selection. Instead, our results suggest that everything else equal, buyers are indifferent or if anything, they might perhaps slightly prefer women (again, this result is not significant).

[Table 7 about here.]

We specify a linear regression model to estimate the effect of gender on total revenue, clustering standard errors at seller level (Table 8). To account for the small number of clusters in our sample, we compute standard errors clustered at the seller level using the Wild bootstrap method described in Cameron, Gelbach and Miller (2008). In Column 1 of Table 8, we simply regress the dichotomous variable male on revenues. Being male has a large but insignificant negative effect on revenues. In Column 2, we add controls for the number of days the seller has participated in the experiment, as well as the type of confederate, since we had both students and surveyors take part in our experiment. We again find that being male is associated with lower revenues and the coefficient is now significant. Columns

3 and 4 mirror the estimates in Columns 1 and 2, with the number of goods sold as the dependent variable. We find that men sell 1.6 fewer goods than women, which corresponds to 23% fewer goods sold. This difference is statistically significant at the 10% level (p=0.08) in the Column 4 specification, where we control for seller type and days worked, using Wild bootstrap standard errors. Overall, being a male seller is associated with a lower business performance once we control for business characteristics and seller's behavior. While the evidence regarding whether women significantly outperform men is mixed, it is clear that men do not outperform women. Rather, female sellers sell and earn as much as their male counterparts, if not more.

[Table 8 about here.]

Women make more than men on average, but this difference masks large disparities in performance. To investigate whether this difference in means is robust to outliers, we additionally run a quantile regression (not shown). The difference in performance persists using a quantile regression at the 25th, 50th and 75th percentiles. However, these differences are not significant, arguably since our sample size is relatively small and so we are underpowered for this type of cut of the data.

The results of this experiment show that buyers' behavior in the marketplace may actually favor female sellers, if women and men run the same business and behave in a scripted way. However, we show that demand-side constraints affect the amount of entrepreneurial labor of female sellers compared to male sellers. Female sellers sell more items, but attract disproportionately more clients who do not purchase.

Having shown that buyer discrimination is not a constraint for women selling goods of observable and identical quality, we turn to a more natural setting to examine the roles of seller and buyer behavior jointly.

4.2 Experiment 2 Results: Gender differences in seller behavior

In Experiment 2, we hold all business characteristics constant but let sellers behave freely with buyers and set prices as they wish. We not only show that with the same business, men and women earn the same, but we also document the patterns of sellers' bargaining and pricing behavior, revealing no gender differences in the way sellers negotiate with buyers.

Figure 5 shows the distribution of revenues earned by men and women while selling at one of our identical stalls for the same time period.

[Figure 5 about here.]

As can be seen, when we experimentally control for business inputs, the distribution of daily revenues for men and women look very similar. We find that women earn as much as men. Combined with the results from Experiment 1, this suggests that buyers do not behave differently based on a seller's gender when the business characteristics are the same, and that bargaining and negotiation does not put women at a disadvantage.

Table 9 presents the performance results for male and female sellers. Women make an average of Rs. 175 in profits, against Rs 168 for men, a difference that is not statistically significant (p=0.42). In terms of revenues, there are also no statistically significant differences between men and women. On average, women earned Rs. 598, against Rs. 596 for men. Although the difference is not statistically significant, it is striking that, on average, women have *higher* profits and revenues. Since male- and female-owned businesses are equally profitable in this experiment, we can conclude that seller behavior and buyer discrimination are not first-order determinants of the gender profit gap in this context.

[Table 9 about here.]

Next, we examine whether men and women price and bargain differently. Our data collection protocols enabled us to assemble a rich dataset containing prices quoted and paid for every single transaction. We test whether male and female sellers offered and charged different prices on average. Our results show that sellers charged similar prices, regardless of gender. Table A3 shows the prices quoted by sellers for each of the four vegetables that we sold in our experiment. Prices are reported in Rupees per kg and correspond to the first quote the seller gave to a prospective buyer. For all vegetables, we find no differences in prices quoted between male and female sellers. Table A4 is analogous to Table A3, but reports final purchase prices after any bargaining has occurred. Since our surveyors could only capture the total transaction amounts, we restrict the sample to one-vegetable transactions. These account for 80% of all transactions. Similarly, we find no gender differences in final prices. Given that male and female sellers perform equally well in this experiment, it is not surprising that they employ similar pricing and bargaining strategies.

Finally, we turn to buyer behavior. We see a small but insignificant difference by gender in the number of buyers who approach the seller to ask for a quote (Table A5). Women receive 48 requests for a quote, against 44 for men, but the p-value is 0.15. Similarly, we see a small but insignificant difference in the number of sales between men and women: women completed 34.4 daily sales, against 31.8 for men (Table A5).

In Experiment 2, using a sample of real experienced sellers, we show that when experimentally controlling for business characteristics, the gender of the seller does not affect business performance. Combined with the results from Experiment 1, this rules out both demand-side constraints and seller behavior as determinants of the gender profit gap. Even when female and male sellers behave in a free, unscripted way, men and women perform the same, if they are given the opportunity to run the same business.

5 Discussion

5.1 Accounting for selection in Experiment 2

In Experiment 2, we offered every seller in our baseline survey the opportunity to participate in the experiment. Due to budget limitations, our experimental shops had to be small in size, and therefore we did not expect all sellers to participate. Take-up was 54% for female sellers and 48% for male sellers.

One might worry about selection into our experiment. As expected, our experiment did not attract the top performers, since the male and female sellers we recruited are among those who earn the least – but this was the case for both men and women. As a consequence, the average performance in our experimental sample was slightly lower than for the representative sample. We are able to document the extent of this selection, since among the participants in our experiment, men report earning 35% more than women ($p<0.001$, Table 2). Among our experimental pool, the gender gap in earnings is lower than in the whole population, but still substantial. Selection only threatens the internal validity of our results if there is gender-differential selection into the experiment, that is, if male and female sellers who participate differ along unobservable characteristics that also affect performance. Given our results, we could be concerned that more low-performing men chose to participate.

To test the extent to which this might play a role, we first restrict our results to participants who made less than a certain threshold. Among the male sellers who participated in our experiment, the highest-performing seller reported making Rs 801 per day. A natural threshold is therefore Rs 801. After restricting our sample to male and female sellers who, in our baseline survey, made less than Rs 801, our results are unchanged. Appendix Table A2 shows that women's profits are on average Rs 6 higher than men's, a very small difference that is not statistically significant.

To further assess the role of selection, we re-estimate our results using inverse probability weighting. We account for selection into the experiment specifying a logit model, and estimate standard errors using the Generalized Method of Moments (GMM). While Table A1 shows that being male leads to slightly higher profits, the magnitudes are very low and the coefficients are not statistically significant. After accounting for selection, we find no gender profit gap, which again suggests that selection is not driving our results.

5.2 What explains the gender profit gap?

Having ruled out two potential constraints to the profitability of female-run businesses – buyer discrimination and gender differences in bargaining and pricing – a natural question arises: what drives the gender profit gap? In both of our experiments, women make as much as men. What our experiments have in common is that we control for all supply-side inputs: once women are given the same business as men, they perform equally well. Hence, one or a combination of these supply-side inputs must explain the gap. The business characteristics that we hold constant in both experiments are hours worked, input costs, location, inventory composition, and inventory quantity. In what follows, we successively review each of these business inputs and discuss which is likely to drive the observed gender disparities. Overall, we believe that the most plausible explanations for the gender profit gap come from differences in capital constraints and location.

First, our survey data documents no statistically significant difference between the hours worked by men and women (see Table 4). If anything, women report working 21 more minutes on average (0.35 hours). Furthermore, our data captures opening and closing times for each business owner's shop, and we find no gender differences in either times. Thus, it seems very unlikely that hours worked play a role in explaining the gender profit gap in this context.

Second, female sellers might face higher costs, particularly at the wholesale market. This could be due to discrimination from the vegetable traders who operate there, or because they do not bargain as successfully as their male counterparts. We find no evidence that this is the case. Our baseline survey elicits the price (in Rs/kg) at which vendors purchased vegetables at the wholesale market. Across 38 of the 43 vegetables for which we have cost data for men and women, we find no evidence that women pay a higher price. For the 5 vegetables for which the differences in cost are statistically significant at the 10% level, the sample size is small (ranging from 4 to 46 observations), so it is difficult to conclude that women are at a disadvantage. Our claim is supported by anecdotal evidence and our observations at the wholesale market. First, transactions between wholesale traders and vegetable vendors are public and observable, which would allow all vendors to learn the day's going rate and compare prices across traders. Second, we observed such transactions ourselves and all prices quoted by a given wholesale trader were the same. Third, our observations are corroborated by the qualitative interviews we conducted with the wholesale traders. Thus, it appears unlikely that female sellers pay a higher price for inventory.

Third, it is possible that female sellers' location is disadvantageous. While we cannot completely rule this out, we think this is unlikely for two reasons. First, while walking around the vegetable markets, we did not observe differences between the locations of male and female shops. If location puts women at a disadvantage, it is not immediately obvious. Second, our baseline survey documents that women's shops receive more prospective clients than men's. If women's shops are located in worse areas of the market, this constraint is not so severe as to prevent them from attracting more prospective buyers than men.

Fourth, women may not be purchasing the right type of inventory. Since women sell on average 7.6 different kinds of vegetables compared to men's 6.1 ($p<0.01$), one would have to argue that women buy too many different types of vegetables and would make more profit by specializing in some vegetables. We find little evidence that men and women specialize in different kinds of produce. One exception is that some men tend to specialize in onions and sell these in very large quantities; however, women also sell onions, albeit in smaller quantities. Excluding male sellers who specialize in onions does not change our baseline results; the gender revenue gap is still large and significant (results not shown). Another exception is that women tend to specialize more in chilies; however, excluding chili sellers again yields similar results. Thus, it does not appear that inventory composition is driving the gender gap.

Finally, we consider the quantity of inventory. There are significant gender differences in the amount of vegetables purchased by sellers at the wholesale market: women's inventory is 40% lower in value than men's (Table 4). We argue that gender differences in access to capital likely explain the gender profit gap. Indeed, women in our sample have fewer sources of credit: among sellers who borrow money to purchase inventory, 89% of women report borrowing from only once source (typically, family), whereas 77% of men report borrowing from two sources (typically, family and moneylenders). Since women in this context disproportionately come from disadvantaged backgrounds, the cost of capital is likely higher for them. Additionally, recent research has shown that even when capital is provided to women for free, it is often diverted to other uses, particularly towards their husbands' businesses (Bernhardt et al., 2019). Whether this is optimal remains an open question. By studying the productivity of plots farmed by men and women in the same household, Udry (1996) finds evidence of inefficient allocation of factors within the household, with women's plots being farmed much less intensely. Similarly, it is possible that the intra-household allocation of capital is inefficient. More research into the capital constraints women face, with specific regard to intra-household dynamics, is necessary to shed light on this.

While lower inventory seems to be the most likely driver of the gender profit gap, it is possible that factors other than access to capital or savings constraints limit women's investment in inventory. For example, women may not purchase as much inventory due to differences in ability, risk-aversion, or ambition. Additionally, women tend to start businesses with lower working and social capital. These unfavorable start-up conditions have long-lasting effects on firm productivity (Fafchamps and Minten, 2001) and could thus explain existing gender differences. While distinguishing these mechanisms is beyond the scope of this paper, it is worth stressing that differences in access to capital would only exacerbate the effects of such factors. If one believes that entrepreneurship is a skill that can be learned, at least partly, lower access to capital would prevent women from ever managing larger inventory, thus also preventing them from learning from such experiences. More research into these factors is necessary to determine what drives women's lower investment in inventory.

6 Conclusion

Overall, our findings show no difference in performance outcomes when female and male business owners face the same structural constraints, ruling out buyers' discrimination and differential seller behavior. By breaking the traditional connection between a seller's gender and business characteristics, our experimental design allows us to illuminate the importance of differential business characteristics as a source of inequality for business performance.

Our two field experiments among small business owners in Jaipur mark an important departure from prior work because they experimentally control for gendered differences in business characteristics. Prior work on gender discrimination in the marketplace was not able to distinguish whether buyers behave differently because of the seller's gender or because of differential business characteristics by gender. In other words, once structural constraints are removed, buyers are indifferent to the seller's gender.

In addition, our experimental approach enables us not only to address the role of buyers' discrimination on the gender profit gap, but also to observe the whole spectrum of interactions between sellers and buyers–beyond looking simply at a sale or a callback. Our methodology allows us to discern whether male and female sellers price and bargain differently. Contrary to the results from the behavioral literature on gender differences in negotiation, we find no difference between the way men and women bargain in this context.

Since we rule out demand-side constraints and seller behavior as potential determinants of the gender profit gap, our results highlight the importance of supply-side constraints. Indeed, in both experiments, when provided with the same business as men, women perform at least as well, if not better. One policy implication is that practitioners may want to renew efforts to provide female entrepreneurs with equal business inputs and opportunities. While the seminal experimental studies by De Mel, McKenzie and Woodruff (2008), De Mel, McKenzie and Woodruff (2009*b*) and Fafchamps et al. (2014) find zero returns to capital for female-owned enterprises, new research by Bernhardt et al. (2019) suggests that, in these experiments, the capital that women received was in fact re-invested into their husbands' businesses. This implies that the returns to capital for female-run businesses are not necessarily zero, as previously estimated. Rather, this research highlights the importance of family financing and intra-household allocation of resources – providing women with access to inputs is not enough for them to use it. In light of this new study, our experiments can be seen as a form of "extreme capital drop" intervention, since we provide capital that is non-transferable in the form of a fully-formed business. Since we find no gender profit gap in both experiments, our results are consistent with positive returns to capital for both men and women. However, our shops are small in scale and our experiments held many supply-side inputs constant, rendering it difficult to determine which of these inputs is the driver of the gender profit gap. We see this as a promising avenue for future research.

In addition, we want to emphasize that we chose a setting in which it is common for both men and women to work. Presumably, seller behavior or buyer discrimination could still matter in other contexts, maybe in particular in occupations where women have only recently started to work. Again, we see this as an interesting question to explore in future work.

Finally, a distinguishing feature of our research is our precise measurement of profits and revenues. While most of the literature on microenterprise profits relies on self-reported measures, we measure revenue directly and precisely by counting cash. In our experiment, we also set costs. Our measures of performance are therefore unique in their precision. Since self-reported measures of profits are subject to considerable measurement error (De Mel, McKenzie and Woodruff, 2009*a*), it is possible that the magnitude of the gap is overestimated due to gender differences in self-reports. This would be the case if, for instance, men tend to overreport profits, while women underreport them. We acknowledge this as a limitation in our current study, and examine this in subsequent work.

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Table 1: Female business owners disproportionately come from disadvantaged backgrounds.

	Mean Female	N(F)	Mean Male	N (M)	Diff M-F	p-val
Age	42.63	113	41.08	109	-1.55	0.34
Number Children	3.48	128	2.63	120	-0.84	0.00
Education (years)	1.16	128	7.23	120	6.07	0.00
Experience (years)	17.88	128	17.55	120	-0.33	0.83
Spouse Works	0.60	121	0.25	118	-0.36	0.00
General Caste	0.02	128	0.25	120	0.23	0.00
OBC Caste	0.34	128	0.38	120	0.05	0.44
Scheduled Caste	0.45	128	0.27	120	-0.19	0.00
Scheduled Tribe	0.18	128	0.07	120	-0.10	0.01
Hindu	0.98	128	0.83	120	-0.14	0.00
Muslim	0.02	128	0.16	120	0.13	0.00

Notes: Observational Data among a representative sample of sellers, prior to our experiment. Column 5 presents the difference between columns 1 and 3. Column 6 presents the p-value from a t-test of differences with robust standard errors.

Table 2: Before our experiment: The gender gap in earning among existing sellers

	Mean Female	N(F)	Mean Male	N(M)	Diff M-F	p-val
Panel A						
Representative Sample						
Daily Revenue	2,432.81	125	4,039.75	117	1,606.94	0.00
Weekly Revenue	11,265.62	127	22,743.74	119	11,478.12	0.00
Monthly Revenue	32,285.47	128	77,536.20	119	45,250.73	0.00
Cash-based revenue	1,195.46	98	1,744.00	70	548.54	0.01
Panel B						
Experiment participants						
Daily Revenue	2,046.47	126	3,054.02	125	1,007.55	0.00
Weekly Revenue	10,748.66	128	18,132.86	125	7,384.20	0.00
Monthly Revenue	34,761.98	128	65,540.87	125	30,778.90	0.00
Cash-based revenue	1,014.41	51	1,540.00	35	525.59	0.03

Notes: This table presents descriptive statistics about the gender gap in earning among a representative sample of existing sellers (Panel A) and among participants in our experiment only (Panel B). Observational Data in Rupees. Column 5 presents the difference between columns 1 and 3. Column 6 presents the p-value from a t-test of differences with robust standard errors. Our final experimental sample of 282 sellers does not overlap exactly with the sellers in our representative sample of 272 sellers. The three first variables are measures of self-reported revenue from our observational survey. The fourth variable, "Cash-based revenue" is a cash estimate of revenue for a portion of the day, that we computed by taking the difference between the cash estimate at the beginning and at the end of the survey, that we measured as follows. Before we started the survey, we asked the business owner how much cash s/he had at that time. At the end, we again asked the owner how much cash she has. All these variables go in the same direction, showing that female business owners report earning significantly less than men. We find the same patterns whether we look at our representative sample of business owners, or at the participants in our experiment only.

Table 3: Before our experiment: The gender gap in earnings among a representative sample of sellers

	(1) Daily Revenue (Rs)	(2) Daily Revenue (Rs)	(3) Daily Revenue (Rs)	(4) Daily Revenue (Rs)
Male	1570.5***	1048.2***	875.9***	980.3***
	(308.5)	(247.4)	(329.4)	(348.5)
Value of Inventory		0.451***	0.418***	0.390***
		(0.0690)	(0.0722)	(0.0737)
Age			-20.71	-21.00
			(15.46)	(14.26)
Education (years)			28.79	22.84
			(40.94)	(45.07)
Experience			6.772	8.811
			(14.18)	(14.96)
Scheduled Caste			-37.96	-73.26
			(476.7)	(448.2)
Scheduled Tribe			177.9	263.5
			(664.9)	(577.2)
OBC Caste			542.5	475.4
			(512.2)	(495.6)
Hindu			-47.29	-27.53
			(552.6)	(583.1)
Observations	242	242	212	212
Mean of Dep. Var. (Male)	4120.9	4120.9	4120.9	4120.9
R squared	0.1000	0.395	0.414	0.451
Market FE	N	N	N	Y

Notes: The unit of analysis in this table is the seller. Male is an indicator variable for the business owner's gender being male. Sample in above regressions include all business owners in our representative sample. Sample size varies slightly across columns due to missing values for some variables. All independent variables are taken from the observational survey. Experience refers to years of experience as vegetable sellers. "Market FE" refers to market fixed effects. Robust standard errors in parentheses $***$ $p < 0.01$, $**$ $p < 0.05$, $*$ $p < 0.1$.

Table 4: Before our experiment: Female-owned businesses are much smaller than male-owned businesses, yet they work a similar number of hours.

	Mean Female	N(F)	Mean Male	N (M)	Diff M-F	p-val
Value of inventory (Rs)	3,308.37	124	4,622.74	118	1,314.37	0.01
Daily cost of all veg (Rs)	3,414.77	124	4,867.96	118	1,453.19	0.01
Hours worked	9.11	88	8.76	56	-0.35	0.56

Notes: Observational Data prior to our experiment. The value of inventory the total amount of inventory at the beginning of the day, valued at the price of purchase at the wholesale market. The daily cost of all veg (Rs) is the business owner's answer when we asked them how much they have spent at the wholesale market that morning. We also asked the business owners to report the self-reported hours on that day. While men have 40% more inventory than women ($p<0.01$), men and women report working a similar number of hours ($p=0.56$).

Table 5: Before our experiment: Buyers are more likely to purchase from male sellers.

	All	N	F Vendors	N(F)	M Vendors	N(M)	Diff M-F	p-val
All Clients	0.78	436	0.72	124	0.81	312	0.09	0.06
Female Clients	0.72	250	0.66	82	0.74	168	0.09	0.18
Male Clients	0.87	186	0.83	42	0.88	144	0.05	0.32

Notes: Observational Data at the transaction-level prior to our experiment. Column 7 presents the difference between columns 3 and 5. Column 8 presents the p-value from a t-test of differences with standard errors clustered at the buyer level. We followed buyers with their consent in the market, as they were making purchases. The dependent variable is 1 if the buyer made a purchase from the stall, 0 otherwise. We successively consider all buyers, only female buyers, only male buyers. Conditional on visiting a stall, buyers are more likely to buy from a male seller ($p<0.1$). We do not know however, whether this is due to the seller's gender or to gendered differences in business characteristics.

Table 6: Experimental Design

	Experiment 1	Experiment 2
Capital (type, quantity and quality of goods)	Fixed	Fixed
Location	Fixed	Fixed
Hours worked	Fixed	Fixed
Seller behavior: Bargaining and price setting	Endogeneous	Fixed
Perceived quality of goods	Endogeneous	Fixed
Buyers' behavior	Endogeneous	Endogeneous

Table 7: Performance Results from Experiment 1

	F Vendors	N(F)	M Vendors	N(M)	Diff M-F	p-val
Revenue	97.50	60	63.33	57	-34.17	0.16
Revenue(Trimmed)	96.73	55	67.36	53	-29.37	0.17
Total Goods Sold	6.89	61	5.21	61	-1.67	0.30
Total Goods Sold (Trimmed)	6.82	56	5.51	57	-1.31	0.35
Total Clients	12.52	61	8.91	58	-3.61	0.09
Total Purchases	5.41	61	4.66	58	-0.75	0.49
% Purchased	0.43	61	0.54	58	0.11	0.00

Notes: Experimental Data. Column 5 presents the difference between columns 1 and 3. Column 6 presents the p-value from a t-test of differences with robust standard errors. Women performed better than men. Female sellers earn more than men on average, but this difference is mainly due to high-performing female outliers, see Figure 4. Women also do more "entrepreneurial labor" since they respond to 41% more queries of buyers. N = 122 seller-days.

Table 8: Women perform better than men, experimentally controlling for business characteristics and seller's behavior

	(1)	(2)	(3)	(4)
	Revenue	Revenue	# Goods Sold	# Goods Sold
Male	-34.167	-32.864**	-1.672	-1.678
	(-1.42)	(-2.16)	(-1.04)	(-1.66)
Observations	117	117	122	119
Mean of Dep. Var. (Women)	97.50	97.50	6.89	6.89
R squared	0.05	0.29	0.03	0.29
Controls	N	Y	N	Y
P-value for the test				
Male=0, Wild Bootstrap	0.27	0.01	0.39	0.08

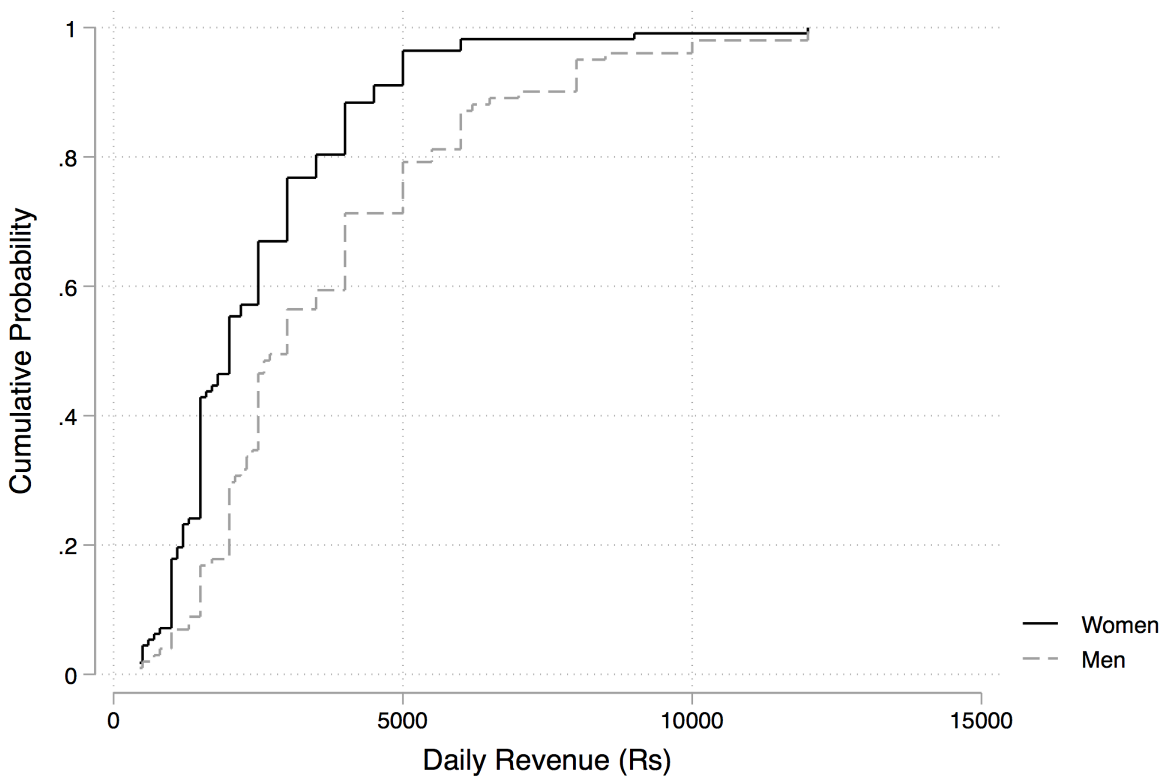
Notes: Experimental Data. Above are regressions where the outcome variable is daily revenue in rupees from Experiment 1, in which we experimentally controlled for seller's behavior and all business characteristics (type, quantity and quality of inventory, as well as hours worked and location). Column 1 is the unconditional effect of being male. Column 2 includes controls for the number of days the participant took part in the experiment, as well as for the type of confederate seller: we had both students and surveyors acting as confederates. Standard errors clustered at the respondent level. We also report p-values for standard errors computed using the wild bootstrap technique described in Cameron, Gelbach and Miller (2008). N = 122 seller-days.

Table 9: Performance Results from Experiment 2

	Mean Female	N(F)	Mean Male	N (M)	Diff M-F	p-val
Profit (Rs)	175.43	137	168.10	135	-7.33	0.42
Revenue (Rs)	598.91	137	569.78	135	-29.13	0.32

Notes: Experimental Data. Column 5 presents the difference between columns 1 and 3. Column 6 presents the p-value from a t-test of differences with standard errors clustered at the seller level. When controlling for business inputs, we find no statistically significant differences between men and women in terms of revenues or items sold, suggesting that buyers' behavior does not negatively affect the earnings of female-owned businesses. N = 272

Figure 1: Before our experiment: The gender gap in earning among existing sellers

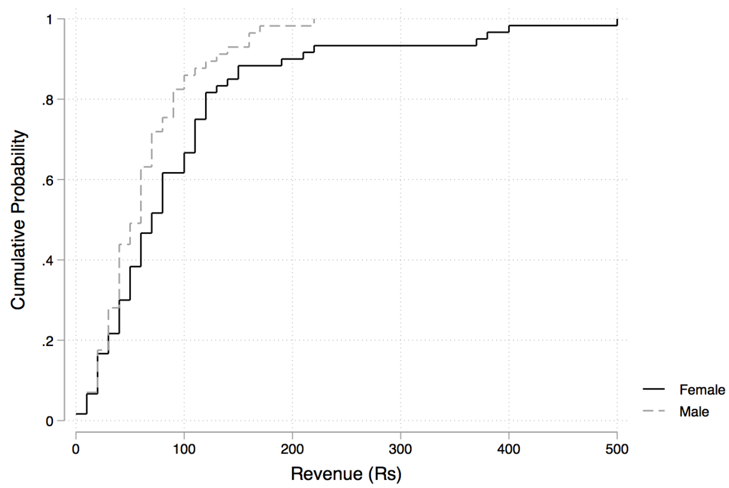


Notes: Observational data among a representative sample of business owners. Female business owners report earning 40 % less than male ($p<0.001$). Two-sample Kolmogorov-Smirnov tests for equality of distribution between men and women: 0.000***. N = 237.

Figure 2: A picture of our two stalls selling packaged goods, respectively with a male seller (left) and a female seller (right)

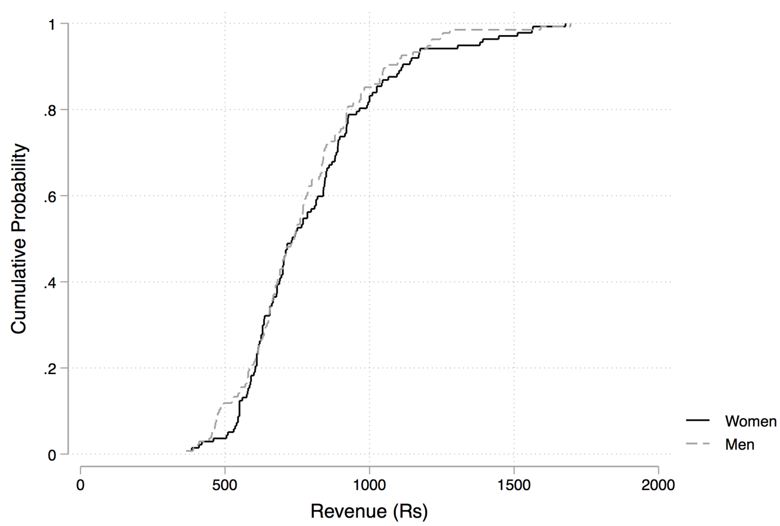
Figure 3: A picture of our two stalls selling vegetables, respectively with a male seller (left) and a female seller (right)

Figure 4: Results from Experiment 1: Female sellers did not underperform compared to male sellers



Notes: Experimental Data data with confederate sellers. Women perform as well, if not better. Female sellers earn more than men on average, but this difference is mainly due to high-performing female outliers. Two-sample Kolmogorov-Smirnov tests for equality of distribution between men and women: 0.113. N = 122 seller-days.

Figure 5: Results from Experiment 2: Controlling for business inputs, men and women earn the same



Notes: When we experimentally control for business inputs, we find that women earned as much as men. Two-sample Kolmogorov-Smirnov tests for equality of distribution between men and women: 0.707. N = 282

Appendix

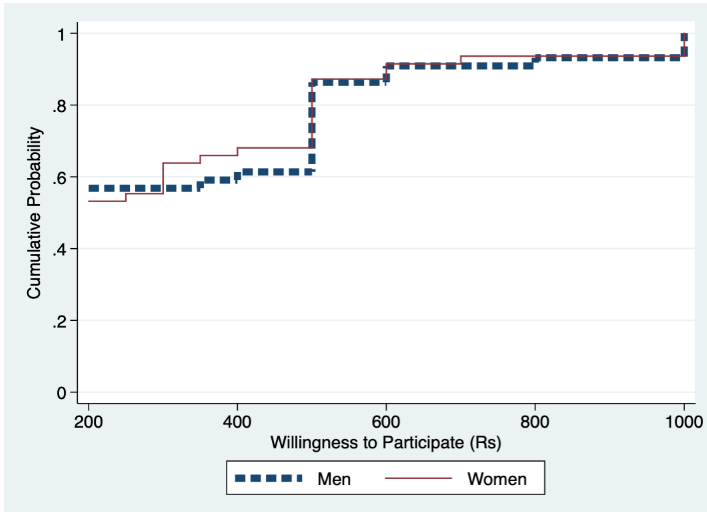
A Experimentally determining the participation fee

Participants were offered a participation fee to take part in our experiment. In the first phase of our study, we determined the amount of the participation fee for sellers through an experimental game, to ensure that the amount was high enough to attract both men and women. Drawing from the Becker-DeGroot-Marschak (BDM) method (Becker, DeGroot and Marschak, 1964), our experimental game elicited the payment required by sellers to come sell in a different market for a day, in a way that was incentive-compatible.

This procedure consisted of asking sellers how much they would be willing to receive to sell in a different market for a day. We asked respondents in increments of Rs. 50, starting at Rs. 200 and going up to Rs. 1000. After having elicited the minimum amount respondents would be willing to receive as a compensation, we then drew a price at random from a distribution of prices in increment of Rs. 50, starting from Rs. 200 and up to Rs. 1000. If the price was above or equal to the minimum amount the respondent said they required to sell in a different market, they were paid this amount and recruited to sell in one of our stalls. If the price drawn was below the minimum amount they would require, they cannot participate in our experiment.

After successful implementation of this procedure in August-September 2017, we were confident that this game was well understood by our target population. The game was administered to a representative subset of sellers, drawn at random within each market. This procedure enabled us to measure a seller's willingness to move to a different market, which is in general not easily quantifiable. The results from this first phase showed us that the participation fee required to take part in our experiment did not differ in a significant manner between men and women (Figure A1). Moving forward, we decided to set the fee at Rs 500, to ensure that enough participants, both men and women, would be willing to come in our stalls. We therefore used this game exclusively in the first phase of our study, to inform the participation fee to attract both men and women in later stages.

Figure A1: Experimentally determining that men and women require similar reservation price to take part in our experiment



Results from our experimental game to determine the participation fee offered to sellers taking part in our experiment. We used the Becker-DeGroot-Marschak (BDM) method to elicit the payment required by sellers to come sell in a different market for a day, in a way that was incentive-compatible. We first asked sellers how much they would be willing to receive to sell in a different market for a day. We then drew a number at random. Participants could only take part in our experiment if the number was below what they said was the minimum required to participate. This figure shows that men and women did not significantly differ in terms of their reservation price to take part in our experiment. N = 129

B Accounting for selection into Experiment 2

Take-up of Experiment 2 was 54% for women and 48% for men. As expected, our experiment attracted the lower-performing business owners. Because of budget constraints, our experimental stalls had to be relatively small in size; thus, expected profits could not be high enough to attract the high-performing businesss owners. To check whether gender-differential selection could be driving our results, we restrict our results to participants who reported making less than Rs 801 in revenue per day in our baseline survey. This threshold corresponds to the revenue made by the highest-performing male seller who participated in our experiment. We refer the reader to section 5.1 for a complete discussion of selection into the experiment.

Table A1: Results are robust to selection: Inverse probability weighting and propensity score estimation

	Selection	Profit	Selection	Profit
Male	0.0886	11.40	0.0564	0.653
	(0.47)	(0.69)	(0.31)	(0.04)
Daily Revenue (Rs)	-0.0000387	-0.0102**		
	(-1.20)	(-2.71)		
Inventory Value			-0.0000405	-0.00356
			(-1.66)	(-0.99)
Num. Veg. For Sale	-0.0148	-1.539	-0.00922	-2.143
	(-0.68)	(-0.55)	(-0.43)	(-0.74)
OBC	-0.258	31.95	-0.289	19.91
	(-0.89)	(1.11)	(-1.00)	(0.67)
SC	-0.136	10.81	-0.148	1.045
	(-0.45)	(0.38)	(-0.49)	(0.04)
ST	-0.0927	5.914	-0.0686	6.783
	(-0.25)	(0.16)	(-0.19)	(0.19)
Hindu	0.553	-49.95	0.513	-44.96
	(1.59)	(-1.34)	(1.47)	(-1.08)
Observations(Selection)	233		237	
Observations(Profit)	96		98	
Mean of Profit (Male)	182.4		182.4	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: We use inverse probability weighting to account for selection into the experiment. Column "Selection" shows our propensity score estimation (probit). "'Profit" presents the results using inverse probability weighting. Models differ on the inclusion of controls and the use of self-reported daily revenue ("Daily Revenue") as opposed to the self-reported value of inventory ("Inventory Value") in the propensity score equation. Overall, our results from the inverse probability weighting show that the equal performance between men and women in Experiment 1 is *not* due to selection. N = 237

Table A2: Results are robust to selection: Restricting the sample to lower performers

	Mean Female	N(F)	Mean Male	N(M)	Diff M-F	p-val
Daily Profit (Rs)	188.54	45	182.70	43	-5.84	0.74
Daily Revenue (Rs)	921.04	45	880.86	43	-40.18	0.50

Notes: Results from Experiment 2, after restricting the sample to sellers who report revenues lower than Rs 801 in our baseline study. Our results are unchanged even among sellers who report similar levels of baseline earnings. This suggests a limited role for selection into the experiment.

C Additional tables and figures

Table A3: Initial price quoted by seller (Rs/kg)

	(1) Tomato	(2) Okra	(3) Cucumber	(4) Peas
Seller Male	0.0172	0.310	0.345	-0.0479
	(0.328)	(0.829)	(0.656)	(0.674)
Observations	6251	3578	1653	1878
Mean of Dep. Var. (Male)	14.47	33.26	13.44	15.41
R squared	0.154	0.252	0.0464	0.0574

Transaction-level data. The dependent variable is the price quoted by the seller, in Rs/kg, for the vegetable named in each column. Standard errors (included in parentheses) are clustered at the seller level. Regressions include market fixed-effects. $***$ p $<$ 0.01, $**$ p $<$ 0.05, $*$ p $<$ 0.1.

Table A4: Final price paid by the client (Rs/kg)

	(1) Tomato	(2) Okra	(3) Cucumber	(4) Peas
Seller Male	0.00756	0.277	0.0165	-0.165
	(0.315)	(0.838)	(0.595)	(0.586)
Observations	3487	1497	856	1050
Mean of Dep. Var. (Male)	13.49	30.73	12.40	13.88
R squared	0.169	0.274	0.0864	0.0983

Transaction-level data. One observation is the purchase of one vegetable (we exclude purchases of two vegetables or more because it is impossible to attribute the total price to more than one vegetable. It is worth noting that single-vegetable transactions represent 80% of all transactions). The dependent variable is the final price, in Rs/kg, for the vegetable named in each column. Standard errors (included in parentheses) are clustered at the seller level. Regressions include market fixed-effects. $***$ p $<$ 0.01, $**$ p $<$ 0.05, $*$ p $<$ 0.1.

Table A5: Number of visits and sales (Experiment 2)

	Mean Vendor F	N(F)	Mean Vendor M	N (M)	Diff M-F	p-val
Total # visits	47.61	127	43.82	128	-3.79	0.15
# female visits	19.91	127	17.14	128	-2.76	0.02
# male visits	30.49	127	29.19	128	-1.30	0.56
Total # sales	34.48	127	31.80	128	-2.68	0.13
For F clients	11.97	127	10.31	128	-1.66	0.03
For M clients	20.42	127	19.29	128	-1.13	0.39
Ratio visits/sales	0.76	127	0.76	128	0.00	0.94
For F clients	0.61	127	0.64	127	0.02	0.40
For M clients	0.70	127	0.70	128	0.00	0.86

Notes: Experimental Data. Column 5 presents the difference between columns 1 and 3. Column 6 presents the p-value from a t-test of differences with robust standard errors. The unit of analysis is a seller. Number of sales is the number of transactions for which a buyer came to the business and purchased products. One sale is the purchase of one or more vegetables. We define a visit as any instance where a buyer asked the seller for the price of a product, whether they subsequently made a purchase or not. N = 255

Figure A2: Our timeline for this research project.

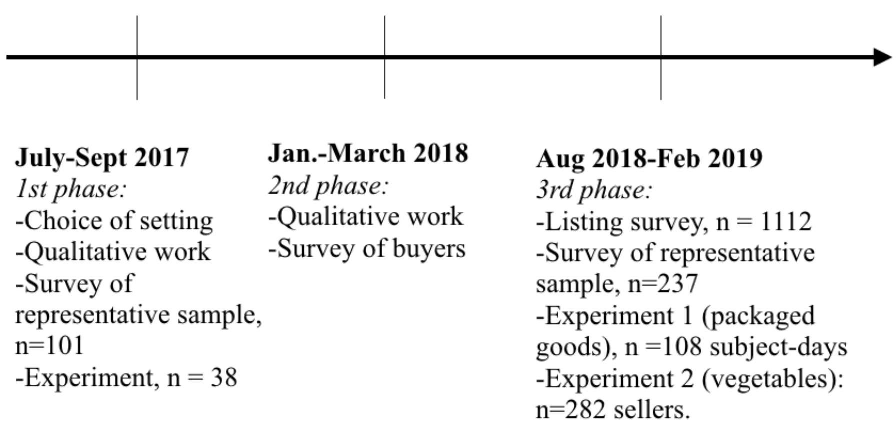


Figure A3: A map of the 13 largest markets in Jaipur, India, that we visited for our listing survey