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ABSTRACT

What accounts for the ubiquity of small vendors operating side-by-side in the urban centers of developing countries? Why don't competitive forces drive some vendors out of the market? We ran an experiment in Kolkata vegetable markets in which we induced (via subsidizing) some vendors to sell additional produce. The vendors earned higher profits, even when excluding the value of the subsidy. Nevertheless, after the subsidies ended vendors largely stopped selling the additional produce. Our results are consistent with collusion and inertial business practices suppressing competition and efficient market exit.

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1 Introduction

Development economists have long noted the ubiquity of small firms operating side-by-side in densely packed urban markets. Lewis (1954) observes that petty retail trading in developing countries is dominated by crowded markets and traders making only few sales each. According to Lewis, consumers would be no worse off if many traders left the market, leaving others to expand. More recently, using data from the Census of Business Establishments in Uganda, Bassi et al. (2021) finds over a dozen industries in which the average firm has more than 64 competitors within 500 meters, and five industries in which the average firm has more than 256 competitors within 500 meters. What accounts for the tight clustering of small firms? Why don't competitive forces cause some firms to lower their prices, increase their scale, and drive competitors out of the market? Does the status quo represent an efficient organization of labor, or could the same demand be served by fewer firms, as Lewis conjectured?

We explore this puzzle in the context of fruit and vegetable vendors in urban India. Our first contribution is to describe novel data on the location, inventory, and sales volume of nearly 1,500 fruit vendors in South Delhi. We establish several facts related to our motivating puzzle. First, vendors operate in close proximity to one another. The average fruit vendor has 3.75 competitors within 25 meters. Second, vendors charge non-trivial markups – the average sale price is between 20 and 30% in excess of procurement costs. Third, vendors have substantial spare capacity. In their busiest hour of a typical week, vendors serve 20 customers on average, and the 90th percentile vendor serves 60 customers. The second and third facts suggest that many vendors could in principle lower their prices and increase their stock in an effort to take market share from competitors. Finally, despite their excess capacity, vendors maintain some degree of product differentiation when compared with immediately-adjacent competitors. We find that for any given fruit a vendor sells, there is on average less than one other vendor selling the same fruit within a 25-meter radius.

What is preventing vendors from stocking additional products, lowering prices, and competing more aggressively? We consider four broad explanations. First, such expansion may not in fact be profitable. Second, expansion may be profitable, but vendors may be subject to capital constraints or lack the relevant knowledge required to procure additional produce. Third, expansion may be profitable, but vendors may not realize this due to imperfect information. Fourth, vendors may know that it is profitable and feasible to expand their product offerings, but may nevertheless not do so. This could be because of implicit or explicit collusion or inertial business practices arising from a variety of behavioral factors.

To differentiate between these explanations, we conducted a (non-randomized) experiment in 20 Kolkata vegetable markets. We recorded prices and quantities for all vendors in all markets for three weeks. Then, in three markets we offered vendors three-week subsidies to procure and stock carrots and peas. We offered the carrot subsidy to all vendors, and the pea subsidy only to those vendors who were not previously frequent pea sellers. The status quo prevailed in the remaining 17 markets. Following the removal of the subsidy, we recorded prices and quantities in all markets for a final three weeks. We use a difference-in-differences approach to estimate the contemporaneous and persistent effects of the subsidies.

Our first finding is that vendors who received the subsidies stocked more peas and carrots during the subsidy period. Vendors tended to sell their expanded stock without cutting prices. As a result, the profits of treated vendors rose significantly. This finding rules out the first explanation above – vegetable vendors could indeed earn higher profits by expanding their inventory, yet this opportunity went unexploited prior to our intervention. It also rules out the second explanation above. Vendors who received the subsidy had to provide the additional capital up-front and were only reimbursed for their purchases later in the day. Hence, by design, all vendors who exploited the opportunity to sell additional peas and carrots must have previously been able to acquire the necessary capital to do so.

Strikingly, after the subsidy period concluded, treated vendors reduced pea and carrot procurement almost to pre-intervention levels. That is, despite having experienced higher profits when they stocked the new products, most vendors reverted to their prior scale of operation.

This second finding speaks against the third explanation above – if limited awareness of profitable opportunities prevented those opportunities from being exploited, we would expect temporary experimentation with those opportunities to lead to more persistent behavioral change (Larcom et al. 2017).

Together, our results suggest that the final explanation above best accounts for vendor behavior, and by implication, why competition does not lead to more market exit. By the end of our intervention, vendors had observed that it would be profitable to expand their product offerings, and they had demonstrated that it was feasible, yet by and large they left the opportunity unexploited.

We conducted qualitative interviews after our intervention to investigate why vendors stopped selling peas and carrots. Many vendors gave answers consistent with implicit or explicit collusion – that there were already too many vendors selling peas or carrots in the market, or that other vendors would be angry. However, these interviews also suggest certain behavioral explanations. It is possible that some vendors did not shift their beliefs despite their experience, or were just averse to change. We discuss these in the concluding section.

There has been a lot of recent interest in the competitiveness of markets in developing countries. The evidence however is somewhat mixed. On one side Bergquist and Dinerstein (2020) finds evidence pointing towards a high degree of collusion among grain traders in Kenya. In an experiment where they subsidize the price of grains to traders, they observe that little of the subsidy gets passed on to buyers. On the other hand, in a similar experiment with cocoa traders in Sierra Leone, Casaburi and Reed (2021) finds that while subsidies to traders do not affect the price offered to buyers, they do affect other benefits offered to buyers. They conclude that these markets are highly competitive.

Similar to those studies, our experiment also subsidizes sellers, but in a setting where conventional wisdom points to high levels of competition: daily, informal markets with many vendors. Our markets have a median of 73 sellers who could all potentially sell the same product, and almost all have excess capacity. Moreover, almost all sellers operate small operations, making it less likely that they have the deep pockets needed to undertake a price war to punish a deviant seller. The evidence in favor of collusion in this setting is therefore perhaps more striking than in Bergquist and Dinerstein (2020). In the last part of our results, we briefly explore how collusion could be sustained in this setting, based on our qualitative interviews. The answer seems to be a flexible social norm rather than outside enforcement.[1]

2 Spatial Competition of Fruit Vendors in South Delhi

We first document several facts about the spatial competition of produce markets, drawn from a census of fruit vendors in South Delhi. Because of the scale and completeness of these data, we are able to draw uniquely confident inferences on several important descriptive facts regarding informal markets. We conducted the census from November 2018 to February 2019 and surveyed all contiguous neighborhoods in a 135 square kilometer area. Our census included 1,179 vendors operating on the street and 309 vendors operating in designated weekly markets. We asked each vendor to carry out a 15-minute survey covering demographics, fruit variety, daily profits and revenues, bargaining, and fruit-level questions on procurement costs, selling prices, and quantities. 80% of vendors consented to the survey. For those that did not consent, we nevertheless have their locations geo-referenced and data on the fruits they were selling based on surveyor observation. We use the census to document four facts that establish our motivating puzzle.

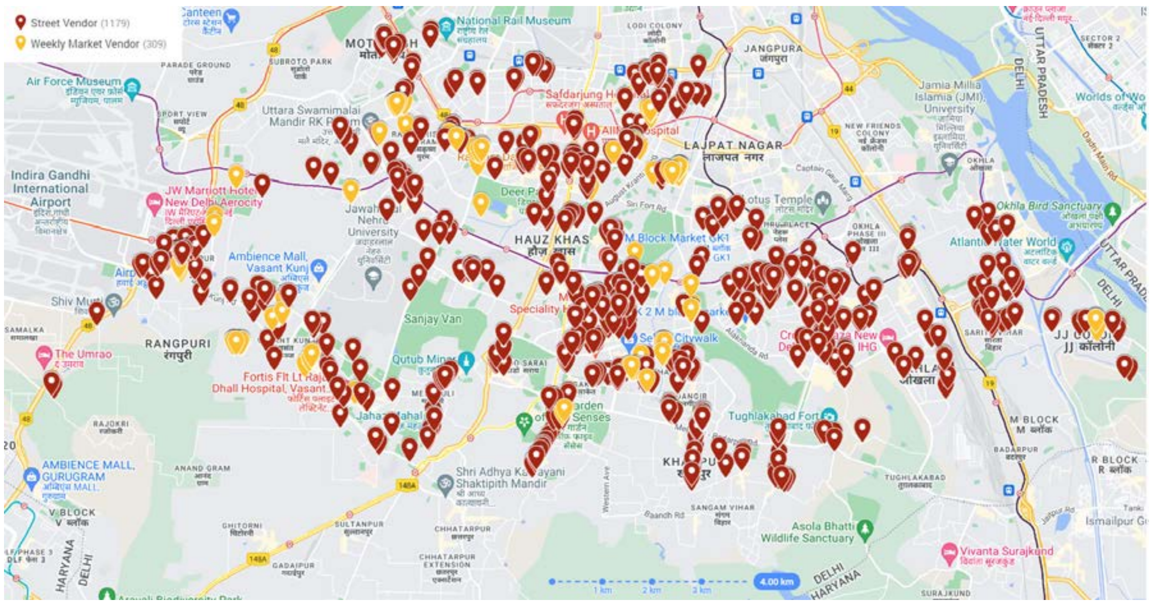
Fact 1: Vendors exhibit a high degree of spatial clustering

Figure 1 maps the universe of vendors in our census area (see Figure A1 for a depiction of

[1] Our paper also relates to the literature examining the extent to which micro and small business growth comes at the expense of competing businesses (De Mel et al., 2008; McKenzie and Woodruff, 2008; Drexler et al., 2014; Cai and Szeidl, 2022). Most closely related is McKenzie and Puerto (2021), which examines the impact of business training on female vendors in rural markets. In that setting, providing training to some entrepreneurs did not negatively impact competitors; rather profits increased at the market level. Similarly, we find that our intervention causes profits to increase at the market level, and we find no evidence of negative spillovers on vendors who did not receive the pea subsidy.

our survey catchment area). Vendors have on average 3.8 other vendors selling fruit within a 25-meter radius, and 1.1 within a 10-meter radius. Furthermore, 27% of vendors have at least one other vendor selling fruit within a five-meter radius. Density is higher for weekly market vendors than street vendors. For example, while 64% of market vendors have at least one other vendor within a ten-metre radius, only 43% of street vendors face such competition.

Figure 1: Fruit Vendor Locations



Notes: The figure denotes the exact locations of 1,179 street vendors (red) and 309 weekly market vendors (yellow). The figure includes vendors that did not consent to answer the census survey. The rectangular area includes some locations outside of our census catchment area. For the exact catchment area, see Figure A1.

Fact 2: Vendors charge non-trivial markups over their marginal cost

Despite operating in close proximity, vendors charge meaningful markups over their procurement costs. Using almost 5,000 vendor-fruit-level observations, we find that the average markup is 29%, measured as the stated selling price of the fruit less the stated procurement cost, as a fraction of the stated procurement cost. After accounting for vendors' expectations about discounts given to customers, markups are still 21% on average. Figure A2 plots the distribution of markups in our data.

While it is difficult to gauge whether these markups are "big" or "small" in an absolute sense, they are sufficiently large that vendors have room to lower their prices to undercut their competitors, if they so desired.

Fact 3: A large fraction of vendors' time is spent sitting idly

As part of our census, we asked how many customers vendors served at various times throughout the day for each day of a typical week. Vendors report a large range of typical customers per hour, with Saturdays busier than weekdays on average, and evenings the busiest, followed by mornings and then afternoons. When considering the maximum typical customers per hour across all three slots, vendors still report a large range, with a median of 15 customers per hour, and a 95th percentile of 42 customers per hour. Figure A3 plots the distribution of customers per hour in our data.

Assuming that all vendors have the capacity to operate at the capacity of the 95th percentile vendor, this suggests that even at their busiest hours the median vendor is operating at less than half capacity.

Fact 4: Nearby vendors maintain a significant degree of product differentiation

Despite a high degree of spatial clustering amongst fruit vendors, the degree of clustering at the fruit-level is considerably smaller. Specifically, averaging over all vendor-fruit-level observations, for any given fruit a vendor sells there is 1.0 other vendors selling the same fruit within a 25-meter radius, and 0.3 within a ten-meter radius. Only 10% of fruits have a vendor selling the same fruit within a five-meter radius. In other words, while fruit vendors are often stationed in close proximity, they are much less often selling identical fruits.

What are we to make of these four facts? Fact 1 establishes the phenomenon that there are many vendors operating in extremely close quarters. Fact 2 establishes that there is room to lower prices, and Fact 3 suggests that vendors have excess capacity to serve additional customers. Why then do vendors not lower their prices to steal market share from their neighbors? Fact 4 deepens the puzzle: even without lowering prices, given their excess capacity, why do vendors not stock the additional products that their neighboring vendors are selling successfully? There are at least four possible explanations within the standard framework of fully-rational profit-maximizing firms.

1. *Expansion would not be profitable*, perhaps because: (i) Customer demand is inelastic due to search costs or loyalty to their existing vendors; (ii) Vendors may not know how to procure additional types of products or judge their quality; or (iii) Vendors may have difficulty overcoming capacity constraints related to transporting produce from wholesale markets or storing it at their stalls.

2. *Vendors know that expansion is profitable but do not have the necessary know-how or cannot afford the investment needed to implement it*. This might be the case if vendors use daily loans to fund procurement and face borrowing constraints (Karlan et al. 2019).

3. *Expansion would be profitable and feasible, but vendors do not realize this*. Imperfect information could drive this behavior in the long-run in the absence of outside intervention (Kremer et al. 2013).

4. *Expansion is individually profitable and feasible, and vendors realise this, but nevertheless refrain from expanding*. Explicit or implicit collusion between vendors or inertial business practices arising from a number of behavioral factors could sustain this behavior in the long run.

We conducted an experiment to distinguish between these explanations.

3 An Experiment to Increase Competition Amongst Kolkata Vegetable Vendors

3.1 Experiment Design

Timeline and Market Selection. Our experiment took place from December 2018 to March 2019 in 20 vegetable markets around Kolkata. Due to the cost of market-wide subsidy interventions we could only intervene in three markets. With so few treated units, we did not randomize. Instead, we chose three markets with two criteria in mind. First, we chose markets of roughly medium size when compared with all 20 markets. Second, we chose markets with relatively little price volatility for peas and carrots. This reduces the possibility of idiosyncratic market-level shocks confounding the subsidy intervention.[2] Our three intervention markets are Charu Market ($n = 45$ vendors), Sarkar Bazar ($n = 73$), and Alam Bazar ($n = 85$).[3]

We break our analysis into three periods: pre-subsidy, subsidy, and post-subsidy. The pre-subsidy period lasted three weeks from December 15, 2018 to January 4, 2019; the subsidy period lasted three weeks from February 23, 2019 to March 15, 2019; and, the post-subsidy period lasted two weeks from March 16, 2019 to March 31, 2019. In each period we collected daily data from all vendors in all 20 markets. The data includes the quantity of all vegetables procured each morning, the quantity sold during the previous day, and the sale price and procurement cost of each vegetable. Given our non-randomized approach, we use this panel data for a difference-in-differences strategy, checking throughout that pre-subsidy period trends on key outcomes are parallel.

[2] Given that there are more markets in our control group than our treatment group, idiosyncratic variation in our outcome variables is more likely to average out in our control group.

[3] Table A1 presents some descriptive statistics on each of our three intervention markets and our 17 control markets. Our intervention markets had 67 vendors on average while our control markets had an average of 85 vendors. Vendors in our intervention markets earned an average of Rs.355/day compared to vendors in control markets with an average daily profit of Rs.520/day. 57% (50%) of vendors in our intervention markets sold peas (carrots), while the corresponding number in control markets is 61% (54%).

Subsidy Intervention. The 17 control markets received no intervention during any of the periods. During the subsidy period, we offered a subsidy to all vendors in the three intervention markets to procure carrots. The subsidy took the form of a cash payment delivered to vendors each morning if they had procured carrots that day. The subsidy value was equal to Rs.20/kg, which was the median procurement cost of carrots during the pre-subsidy period. The maximum quantity subsidized was randomized at the vendor-level each week to be either low or high. Vendors who received the low subsidy were compensated for a maximum of 2kg of carrots, while the high quantity was set at the median of the distribution of daily wholesale purchases of carrots during the pre-subsidy period, for each market (7kg in Charu market, and 5kg in Sarkar Bazar and Alam Bazar).

While we offered the carrot subsidy to all vendors in intervention markets, we only offered the pea subsidy to infrequent pea sellers – the 40% of vendors who sold peas in fewer than eight of the days during the pre-subsidy period. The pea subsidy value was equal to Rs.30/kg, which was the median procurement cost of peas during the pre-subsidy period, and once again the subsidized volume was either low or high. Like carrots, the low quantity was set at 2kg, and the high quantity was set at the median of the distribution of daily wholesale purchases of peas during the pre-subsidy period, for each market (8kg in Charu market, 6kg in Sarkar Bazar, and 10kg Alam Bazar).

The weekly randomization of subsidized quantity was intended for a separate line of inquiry about inframarginal subsidies and income effects. As it is not central to our analysis, we pool vendors who received a high versus low subsidy and focus only on the market-level variation in whether vendors were offered the subsidy or not. This approach maximizes our power to distinguish between the explanations above for limited competition between vendors.

Finally, we introduced one universal (carrots) and one non-universal (peas) subsidy for two reasons. First, we wanted to ensure that all vendors in intervention markets received at least one subsidy to minimize the likelihood of vendors feeling they were treated unfairly. Second, the two different subsidies allow us to explore the effects of two margins of vendor expansion.

The pea subsidy effectively stimulates the "entry" of new vendors who previously did not sell the product and allows us to explore business stealing or other spillover effects on incumbent vendors. In contrast the carrot subsidy also induces incumbents to expand their inventory on the intensive margin, which illuminates whether vendors are effectively constraining the supply of even the goods they have chosen to sell.

3.2 Empirical Approach

We estimate the following specification:

$$y_{imt} = \alpha + \beta_1 During_t + \beta_2 Post_t + \beta_3 Treat_m + \gamma_1 During_t \times Treat_m + \gamma_2 Post_t \times Treat_m + \varepsilon_{imt} \quad (1)$$

where y_{imt} is the outcome of interest for vendor i in market m on day t. $During_t$ is a dummy taking a value of one if day t was during the subsidy period, $Post_t$ is a dummy taking a value of one if day t was after the subsidy period, and $Treat_m$ is a dummy taking a value of one if market m is one of the three intervention markets. This is a difference-in-differences model where our coefficients of interest are γ_1, capturing the effect of our subsidies during the subsidy period, and γ_2, capturing the persistent effect of our subsidies after the subsidy period had ended.

Because we only have twenty markets with three treated, traditional econometric inference based on large-sample asymptotics is unlikely to perform well in our setting. Instead, we report p-values and confidence intervals computed using the wild bootstrap (Cameron et al., 2008; Roodman et al., 2019), and p-values computed using Fisher's permutation test (Fisher, 1936; Young, 2019),[4] both using markets as the relevant cluster unit. While our tables report the results from both inference approaches, the two approaches largely coincide. Given this, we report the wild bootstrap estimates in the text, and note the permutation test p-values only when

[4]With 20 markets, there are 1,140 possible combinations of three intervention markets. For the permutation test, we re-run a given regression 1,140 times, each time using a different unique combination of hypothetical intervention markets. We then calculate p-values as the fraction of t-statistics larger in magnitude than the t-statistic from the original regression.

the two methods differ in statistical significance at conventional levels.

4 Results

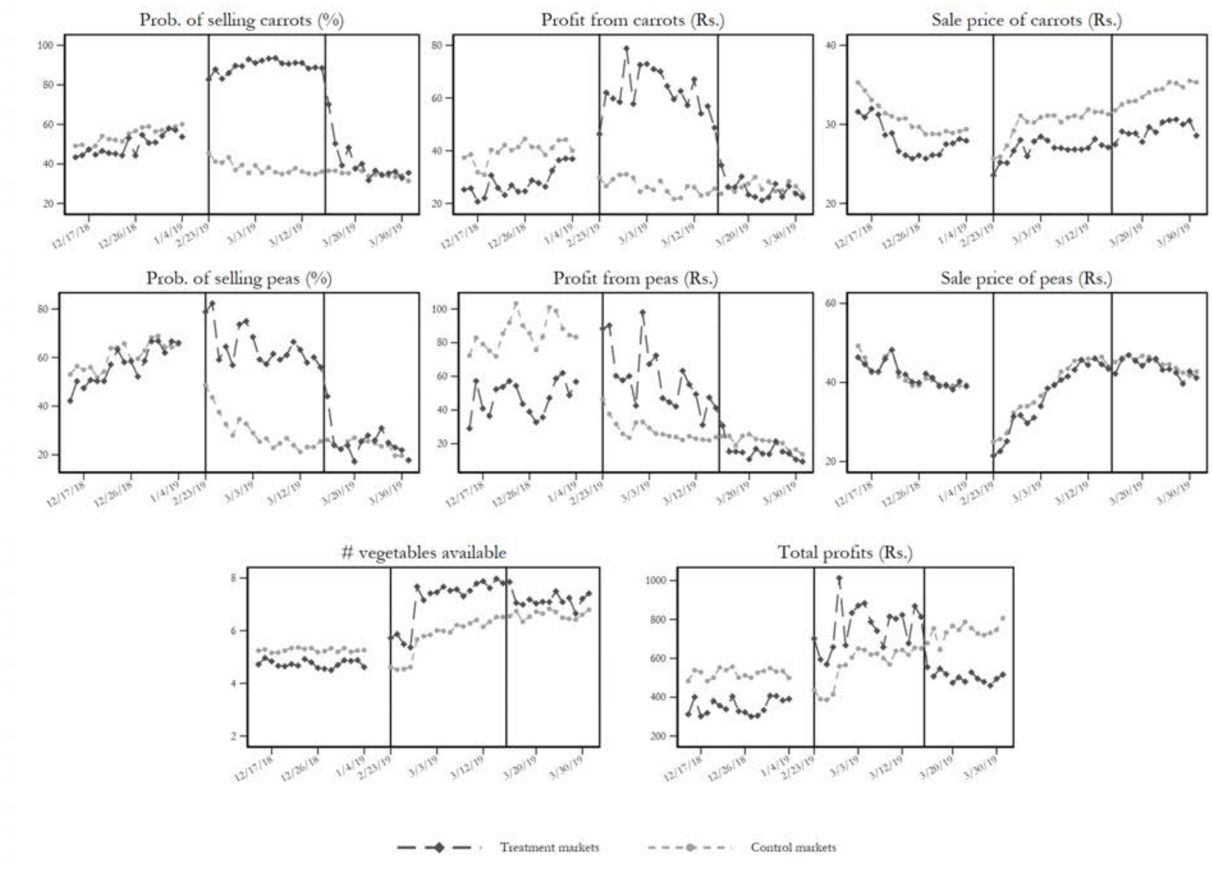


Figure 2: The first row plots the probability a vendor sells carrots, the daily profits accruing from the sales of carrots, and the vendor's anticipated sale price of carrots. The second row plots the same three outcomes for peas. The third row plots the number of types of vegetables a vendor stocks on a given day, and his or her daily total profits. The first vertical line demarcates the start of the subsidy period and the second line demarcates the end of the subsidy period. Profits are calculated as: (amount of vegetable at the start of the day - amount left over at the end of the day)*anticipated sale price - (amount procured at the start of the day * procurement cost). On days where the amount left over was not observed, we impute the vendor's average amount left over all days in which it was measured. Our measure of profit does not include the subsidy vendors received as part of our intervention.

Graphical Summary. Figure 2 summarizes our main findings graphically. First, outcomes in the intervention markets trend similarly to those in the control markets in the pre-subsidy period.

We never reject the null that the trends are parallel (Table A2). Second, the subsidies had an important effect during the subsidy period. Vendors in intervention markets were more likely to sell peas and carrots and had higher average profits from the sales of peas and carrots. They also had higher overall profits during the subsidy period. In contrast, prices in intervention markets trended similarly to those in control markets. Third and finally, the effects of our subsidies largely disappeared in the post-subsidy period.

The Subsidy Period. During the subsidy period, vendors in intervention markets were 57 percentage points more likely to sell carrots on any given day (95% CI: 38pp – 73pp, $\hat{\gamma}_1$ in column 1, Table 1) and 39 percentage points more likely to sell peas (95% CI: 18pp – 64pp, column 5). On average vendors in intervention markets procured an extra 6.0kg of carrots per day (95% CI: 3.8kg – 7.7kg, column 3) and an extra 6.7kg of peas (95% CI: 3.7kg – 11.3kg, column 7). These are substantial increases relative to average procurement volumes of 3.4kg of carrots and 5.9kg of peas in intervention markets in the pre-subsidy period.[5]

Importantly, even without accounting for the value of our subsidy, profits for vendors in intervention markets increased during the subsidy period. Profits from carrots increased by Rs.44.8 per day (95% CI: Rs.20.8 – Rs.57.7, column 4) compared to an average profit from carrots of Rs.25.4 per day in the pre-subsidy period. Profits from peas increased by Rs.59.7 per day (95% CI: Rs.14.7 – Rs.102.5, column 8) compared to an average profit from peas of Rs.47.7 per day in the pre-subsidy period.

In addition, there is no evidence that our intervention caused sale prices for peas and carrots to decline (columns 2 and 6), indicating that vendors had not been meeting customers' full demand prior to our intervention. Thus vendors can expand profitably without reducing prices.

[5] Indeed, these point estimates suggest that vendors increased their average procurement of peas and carrots by more than the average subsidized quantity. This may be because once a vendor is induced to procure any positive quantity of peas or carrots (or induced to continue procuring peas or carrots if they would otherwise have ceased doing so), they find it worthwhile to procure more than the subsidized quantity. This would be reasonable behavior, for example, if they have negotiated a temporary exemption from a collusive norm during the experiment, and want to take full advantage of it.

Table 1: Subsidy Impacts: Carrots and Peas

	Carrots				Peas			
	Prob. of selling (%)	Sale price (Rs.)	Wholesale qty. bought (kg)	Profit (Rs.)	Prob. of selling (%)	Sale price (Rs.)	Wholesale qty. bought (kg)	Profit (Rs.)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_3: Treat	-0.05	-2.62	-1.40	-12.71	-0.04	-0.01	-2.53	-33.29
	[-0.326, 0.239]	[-8.467, 2.721]	[-3.891, 1.198]	[-28.787, 7.978]	[-0.317, 0.249]	[-3.760, 3.522]	[-6.935, 2.336]	[-82.570, 14.097]
	{ 0.642 }	{ 0.078 }	{ 0.306 }	{ 0.296 }	{ 0.549 }	{ 0.986 }	{ 0.085 }	{ 0.070 }
	⟨ 0.603 ⟩	⟨ 0.148 ⟩	⟨ 0.264 ⟩	⟨ 0.142 ⟩	⟨ 0.604 ⟩	⟨ 0.989 ⟩	⟨ 0.148 ⟩	⟨ 0.049 ⟩
γ_1: Treat x During	0.57	-0.44	5.99	44.75	0.39	-0.81	6.72	59.67
	[0.384, 0.727]	[-3.181, 2.222]	[3.768, 7.708]	[20.801, 57.683]	[0.175, 0.638]	[-4.124, 2.750]	[3.685, 11.338]	[14.728, 102.473]
	{ 0.001 }	{ 0.624 }	{ <0.001 }	{ 0.002 }	{ 0.022 }	{ 0.786 }	{ 0.015 }	{ 0.032 }
	⟨ <0.001 ⟩	⟨ 0.685 ⟩	⟨ <0.001 ⟩	⟨ 0.002 ⟩	⟨ 0.002 ⟩	⟨ 0.686 ⟩	⟨ <0.001 ⟩	⟨ 0.002 ⟩
γ_2: Treat x After	0.10	-2.04	1.94	8.79	0.05	-0.87	2.58	26.52
	[-0.111, 0.246]	[-7.991, 4.762]	[-0.106, 3.977]	[-13.216, 29.247]	[-0.220, 0.255]	[-4.334, 2.307]	[-1.077, 8.142]	[-19.606, 66.943]
	{ 0.423 }	{ 0.153 }	{ 0.071 }	{ 0.268 }	{ 0.490 }	{ 0.573 }	{ 0.072 }	{ 0.081 }
	⟨ 0.354 ⟩	⟨ 0.188 ⟩	⟨ 0.192 ⟩	⟨ 0.201 ⟩	⟨ 0.546 ⟩	⟨ 0.533 ⟩	⟨ 0.069 ⟩	⟨ 0.055 ⟩
Pre-subsidy intervention market mean	0.49	27.91	3.43	25.41	0.57	41.80	5.94	47.73
Wild Bootstrap p-value: $\gamma_1 = \gamma_2$	<0.001	0.308	0.001	0.003	0.004	0.965	0.005	0.008
Fisher p-value: $\gamma_1 = \gamma_2$	0.002	0.357	<0.001	<0.001	0.002	0.977	0.003	0.023
N vendors	1631	1470	1631	1631	1631	1489	1631	1631
Observations	55218	25073	55218	55213	55243	22657	55243	55241

Notes: This table estimates specification 1 on our full sample. Coefficients for During and Post not shown. 95% wild bootstrap confidence intervals are in [], wild bootstrap p-value is in { }, and Fisher permutation p-value is in ⟨⟩. Columns 1 - 4 present outcomes for carrots, and 5 - 8 for peas. The outcome in columns 1 and 5 is whether the vendor sells carrots or peas on the given day, the outcome in columns 2 and 6 measure the vendor's anticipated sale price for the relevant vegetable, the outcome in columns 3 and 7 measure the wholesale quantity procured of the relevant vegetable, and the outcome in columns 4 and 8 measure the daily profits accrued from the relevant vegetables. Profits are calculated by computing (amount of vegetable at the start of the day - amount left over at the end of the day)*anticipated sale price - (amount procured at the start of the day * procurement cost). On days where amount left over was not observed, we impute the vendor's average amount left over all days in which it was measured. Our measure of profit does not include the subsidy vendors received as part of our intervention.

Collectively, the results from the subsidy period speak against the first explanation of Section 2: it appears that the sale of peas and carrots *is* profitable, and as we will show below, doing so increases total average vendor profits as well.

These results also rule out the second explanation from Section 2. Subsidized vendors in our intervention markets were required to procure the additional produce without our assistance: they provided the additional capital up-front and were only reimbursed later in the day. Moreover, the average outlay for the additional carrots was Rs.116, and for peas it was Rs.197, considerably less than the average vendor's daily profits of Rs.355. Hence clearly vendors could acquire additional peas or carrots on their own, outside the context of our experiment.

After the Subsidy Ended. The impacts of the subsidy diminished or fully disappeared after the subsidy period ended. There is no statistically significant increase in the likelihood that vendors in intervention markets sell additional carrots or peas ($\hat{\gamma}_2$ in columns 1 and 5, Table 2). Vendors in intervention markets only procured an additional 1.9kg of carrots per day (95% CI: -0.1kg – 4.0kg and only procured an additional 2.6kg of peas (95% CI: -1.1kg – 8.1kg). Profits from selling carrots were only Rs.8.8 higher per day (95% CI: Rs.-13.2 – Rs.29.2) and Rs.26.5 higher per day for peas (95% CI: Rs.-19.6 – Rs.66.9). All of these figures are statistically significantly lower than the corresponding estimates during the subsidy period.

We note that 90% of vendors in intervention markets who sold peas and carrots experienced positive profits from sales of those vegetables during the subsidy period. Hence these results are not driven by the possibility that a majority of vendors found it marginally unprofitable to sell peas and carrots and only those who experienced the profit increase continued selling peas and carrots. Rather, many vendors who experienced positive profits from sales of peas and carrots nevertheless chose to stop selling these vegetables after our intervention concluded.

The lack of persistence speaks against the third explanation of Section 2: if incomplete information alone prevents profitable deviations, experience of profitable expansion should lead to persistent changes in procurement.

Table 2: Subsidy Impacts: Vendor-Level Outcomes

	Main Outcomes - Aggregate			
	Total Cost of Wholesale Purchases (Rs.)	Sales (Rs.)	Profits (Rs.)	# vegetables available
	(1)	(2)	(3)	(4)
β_3: Treat	-448.49	-589.02	-140.53	-0.50
	[-955.904, 84.278]	[-1438.216, 203.759]	[-319.234, 141.657]	[-2.898, 1.997]
	{ 0.055 }	{ 0.067 }	{ 0.132 }	{ 0.536 }
	⟨ 0.032 ⟩	⟨ 0.030 ⟩	⟨ 0.076 ⟩	⟨ 0.472 ⟩
γ_1: Treat x During	689.60	917.98	228.32	1.97
	[247.024, 1176.953]	[150.374, 1529.121]	[-41.246, 528.411]	[0.606, 3.150]
	{ 0.020 }	{ 0.039 }	{ 0.060 }	{ 0.022 }
	⟨ <0.001 ⟩	⟨ 0.006 ⟩	⟨ 0.025 ⟩	⟨ 0.013 ⟩
γ_2: Treat x After	527.12	466.27	-60.84	1.16
	[-137.983, 1061.447]	[-312.903, 1286.565]	[-364.394, 253.049]	[-0.552, 2.626]
	{ 0.295 }	{ 0.335 }	{ 0.329 }	{ 0.289 }
	⟨ 0.268 ⟩	⟨ 0.343 ⟩	⟨ 0.404 ⟩	⟨ 0.229 ⟩
Pre-subsidy intervention market mean	825.12	1167.30	342.18	4.73
Wild Bootstrap p-value: $\gamma_1 = \gamma_2$	0.566	0.153	0.036	0.062
Fisher p-value: $\gamma_1 = \gamma_2$	0.583	0.139	0.002	0.060
N vendors	1628	1628	1628	1628
Observations	52898	52898	52898	52898

This table estimates specification 1 on our full sample. Coefficients for During and Post not shown. 95% wild bootstrap confidence intervals are in [], wild bootstrap p-value is in {}, and Fisher permutation p-value is in ⟨⟩. The outcome in column 1 is the total cost of wholesale purchases on a given day, the outcome in column 2 is the vendor's total revenues on a given day accruing from all produce, the outcome in column 3 is the daily profits accrued from all produce, and the outcome in column 4 is the number of distinct types of vegetables a vendor has available on a given day. Profits are calculated by computing (amount of vegetable at the start of the day - amount left over at the end of the day)*anticipated sale price - (amount procured at the start of the day * procurement cost). On days where amount left over was not observed, we impute the vendor's average amount left over all days in which it was measured.

Beyond Carrots and Peas. Table 2 presents the impact of our subsidies on aggregate vendor outcomes, rather than those corresponding to either carrots or peas. The aggregate picture is largely consistent with the results from the individual vegetables. During the subsidy period, total costs of wholesale purchases in intervention markets rose by Rs.690 per day (95% CI: Rs.247 – Rs.1,178, column 1) compared to an average cost of wholesale purchases of Rs.825 in intervention markets in the pre-subsidy period. Average vendor profits rose by Rs.228 per day (95% CI: Rs.-41 – Rs.528, column 3) compared to an average profit of Rs.342 in the pre-subsidy period. On average vendors stocked an additional 2.0 (95% CI: 0.6 – 3.2, column 4) types of vegetables during the subsidy period compared to an average of 4.7 products stocked per vendor in the pre-subsidy period. Once again, these effects either diminish or disappear after our subsidy concluded, with no statistically significant increase on any of the aforementioned outcomes.

Interestingly, the effect of our intervention on total profits is larger than the sum of the effects on the profits from sales of peas and carrots. This difference is only statistically significant at the 10% level when using the wild bootstrap, and not statistically significant at the 10% level using the Fisher permutation test. Similarly, the effect on the cost of total wholesale purchases is larger than the sum of the effect on the costs of purchases of peas and carrots. This difference is statistically significant at the 10% level using both the wild bootstrap and Fisher permutation tests. Hence these results leave open the possibility that our subsidy "crowded in" the sale of complementary produce.

Pea-Subsidy Impacts by Eligibility. Recall that while everyone in intervention markets received a carrot subsidy, only infrequent peas sellers were eligible for the pea subsidy. We now turn to the differential effects of the pea subsidy on vendors in intervention markets who did and did not receive the subsidy to focus on the extensive margin. These are presented in Table 3, which again uses specification 1, but now splits the sample by pea subsidy eligibility.

Table 3: Subsidy Impacts: By Pea Subsidy Eligibility

	Eligible				Ineligible			
	Prob. of selling (%) (1)	Sale price (Rs.) (2)	Wholesale qty. bought (kg) (3)	Profit (Rs.) (4)	Prob. of selling (%) (5)	Sale price (Rs.) (6)	Wholesale qty. bought (kg) (7)	Profit (Rs.) (8)
β_3: Treat	-0.03	0.38	-1.00	-17.39	0.01	-0.05	-2.87	-37.71
	[-0.063, 0.036]	[-10.561, 16.807]	[-2.234, 0.404]	[-45.451, 20.239]	[-0.098, 0.106]	[-4.282, 3.414]	[-9.154, 3.420]	[-100.073, 29.648]
	{ 0.108 }	{ 0.848 }	{ 0.087 }	{ 0.113 }	{ 0.785 }	{ 0.960 }	{ 0.318 }	{ 0.084 }
	⟨ 0.053 ⟩	⟨ 0.909 ⟩	⟨ 0.061 ⟩	⟨ 0.033 ⟩	⟨ 0.793 ⟩	⟨ 0.961 ⟩	⟨ 0.268 ⟩	⟨ 0.104 ⟩
γ_1: Treat x During	0.66	4.35	7.84	65.59	0.16	-2.00	5.37	50.90
	[0.540, 0.744]	[0.898, 9.646]	[4.118, 10.349]	[32.498, 101.317]	[-0.066, 0.508]	[-5.723, 1.626]	[0.830, 11.139]	[-5.065, 105.568]
	{ <0.001 }	{ 0.035 }	{ <0.001 }	{ 0.002 }	{ 0.073 }	{ 0.318 }	{ 0.040 }	{ 0.054 }
	⟨ 0.003 ⟩	⟨ 0.182 ⟩	⟨ 0.006 ⟩	⟨ 0.009 ⟩	⟨ 0.125 ⟩	⟨ 0.311 ⟩	⟨ 0.008 ⟩	⟨ 0.019 ⟩
γ_2: Treat x After	0.09	0.25	1.74	19.36	-0.00	-0.56	2.66	27.51
	[-0.023, 0.215]	[-3.845, 3.388]	[0.378, 3.430]	[-15.701, 44.486]	[-0.244, 0.214]	[-4.478, 3.074]	[-2.446, 8.733]	[-42.385, 95.720]
	{ 0.070 }	{ 0.904 }	{ 0.033 }	{ 0.108 }	{ 0.945 }	{ 0.782 }	{ 0.239 }	{ 0.170 }
	⟨ 0.121 ⟩	⟨ 0.914 ⟩	⟨ 0.010 ⟩	⟨ 0.013 ⟩	⟨ 0.970 ⟩	⟨ 0.754 ⟩	⟨ 0.274 ⟩	⟨ 0.251 ⟩
Pre-subsidy intervention market mean	0.18	39.38	1.63	10.56	0.85	42.15	8.98	73.99
Wild Bootstrap p-value: $\gamma_1 = \gamma_2$	0.001	0.227	<0.001	<0.001	0.041	0.620	0.038	0.050
Fisher p-value: $\gamma_1 = \gamma_2$	<0.001	0.539	0.007	0.009	0.025	0.554	0.044	0.060
N vendors	562	480	562	562	1069	1009	1069	1069
Observations	19763	3687	19763	19761	35480	18970	35480	35480

Notes: This table estimates specification 1 on our full sample. Coefficients for During and Post not shown. 95% wild bootstrap confidence intervals are in [], wild bootstrap p-value is in {}, and Fisher permutation p-value is in ⟨⟩. Columns 1 - 4 present outcomes for vendors who were eligible for the peas subsidy, and 5 - 8 for vendors who were ineligible for the peas subsidy. The outcome in columns 1 and 5 is whether the vendor sells peas on the given day, the outcome in columns 2 and 6 measure the vendor's anticipated sale price for peas, the outcome in columns 3 and 7 measure the wholesale quantity of peas procured, and the outcome in columns 4 and 8 measure the daily profits accrued from peas. Profits are calculated by computing (amount of peas at the start of the day - amount left over at the end of the day)*anticipated sale price - (amount procured at the start of the day * procurement cost). On days where amount left over was not observed, we impute the vendor's average amount left over all days in which it was measured. Our measure of profit does not include the subsidy vendors received as part of our intervention.

The qualitative patterns for eligible pea vendors are the same as in the previous analyses. During the subsidy period, eligible vendors in intervention markets were 66 percentage points (95% CI: 54pp – 74pp) more likely to stock peas on any given day during the subsidy period, they procured an extra 7.8kg of peas per day (95% CI: 4.1kg – 10.3kg), and earned an extra Rs.65.6 per day (95% CI: Rs.32.5 – Rs.101.3) from the sale of peas. Unlike in the previous analysis, there is evidence of a price increase during the subsidy period of Rs.4.4/kg (95% CI: Rs.0.9 – Rs.9.6), statistically significant at the 5% level using the wild bootstrap, but not when using the permutation test. Qualitative evidence we collected suggests this may be because vendors substituted towards higher quality peas. Once again, all of these effects diminish considerably after our subsidy was removed.

We find no evidence of business stealing effects. In fact, the patterns for vendors who were ineligible for the pea subsidy are largely the same as the patterns for eligible vendors. These vendors procured more peas and earned higher profits from the sale of peas (and higher profits overall, not reported in the table) during the subsidy period, despite not having access to a pea subsidy. Qualitative evidence we collected after the intervention suggests that this is due to informal arrangements between vendors who sold peas prior to our intervention, typically larger vendors, and vendors who did not. Namely, these larger vendors would procure and transport additional peas at the wholesale market and then sell them to vendors who received a subsidy. Note however that this remains consistent with our basic narrative. It is possible for many vendors to increase their sales volume and profits by purchasing and selling more carrots and peas, but even after directly verifying and experiencing these opportunities firsthand, they refrained from exploiting them after our intervention.

For completeness, in Appendix Table A3 we present analogous results from the carrot subsidy, disaggregated by vendors who were frequent or infrequent carrot sellers in the pre-subsidy period. The results are qualitatively the same. Both types of vendors experienced an increase in sales and profits of carrots during the subsidy period, and then these increases largely disappeared in the post period.

Therefore, on the extensive margin, subsidizing the entrance of new pea vendors increased their profits while also increasing the average profits of incumbent pea vendors. On the intensive margin, inducing existing carrot vendors to expand their supply, while also inducing the entry of new carrot vendors, increased the profits of both groups. In both cases, the additional sales and profits largely dissipated after our intervention concluded.

5 Discussion and Conclusion

Given the ubiquity of vendors operating in close proximity to one another, their apparent ability to lower prices and their apparent excess capacity, what is preventing vendors from stocking additional products, lowering prices, and competing more aggressively? We have considered four potential explanations. First, competing more aggressively would not be profitable. Second, competing more aggressively would be profitable but vendors do not have the capital or know-how necessary to exploit this opportunity. Third, competing more aggressively would be profitable and feasible, but vendors are unaware of this opportunity. Fourth, vendors know that competing more aggressively would be profitable and feasible, yet they nevertheless refrain from competition, due to implicit or explicit collusion, or inertial business practices arising from a variety of behavioral phenomena.

The evidence points away from the first three explanations. Vegetable vendors in Kolkata earned higher profits on average when they stocked additional peas and carrots, ruling out the first explanation. While we subsidized the procurement of additional peas and carrots, vendors were required to use their own capital and know-how to purchase the produce and were subsequently reimbursed, ruling out the second explanation. After our subsidy period had concluded, vendors largely stopped selling the additional peas and carrots, despite having experienced earning higher profits from selling additional peas and carrots. This casts doubt on the third explanation, though perhaps does not fully rule it out (for reasons we discuss below).

We are left with the fourth explanation, which prompts a question: why would vendors avoid behaviors that they have experienced and were profitable? To explore this, we conducted a qualitative survey with all vendors in intervention markets who stopped selling peas and carrots after our subsidy concluded. We read a list of 16 reasons a vendor may have stopped selling a product, and for each asked them to tell us whether this reason had no influence, a small influence or a big influence on their decision.

About half of vendors (46% of pea vendors and 42% of carrots vendors) report answers consistent with collusion as being either a small or big influence. Some of the specific responses categorized as such include that there are too many other vendors in the market already selling these products, or that other vendors would be angry if they were to stock these additional products indefinitely.

On the other hand, a majority of vendors (77% of peas vendors and 85% of carrots vendors) also report answers consistent with uncertainty about whether it would be profitable to sell peas or carrots as being either a small or big influence. Some of the specific responses categorized as such include that they were worried about setting the appropriate price for the vegetable, about getting poor quality produce from the wholesaler, or being charged too much. This suggests the possibility that even though many vendors experienced an increase in their profits during our subsidy period, they may not have recognized that their profits exceeded the counterfactual in which they had not stocked the additional produce, which would be a variant of our third explanation. This is consistent with evidence that micro-entrepreneurs may not learn about the most profitable business practices despite exposure to them, due to persistent inattention (Hanna et al., 2014). These responses may also be consistent with loss aversion, in that despite vendors having experienced higher profits during the subsidy period, the possibility of small losses in the future is sufficient to deter them from changing their practices (e.g. Kremer et al., 2013).[6]

[6] A final possibility is that identity played a role in our findings (Akerlof and Kranton 2000; Oh 2021). Specifically, vendors may have stopped selling the additional produce because their identity as a vendor is tied to the types of produce they procure and sell. However, our evidence does not support this explanation. Appendix Table A3 demonstrates that when we subsidized existing carrot sellers to sell additional carrots, they did so and earned higher profits, yet they nevertheless returned to their unsubsidized levels after the subsidy was removed. Presumably selling additional carrots would not challenge their identity, and therefore identity alone cannot explain why vendors ceased selling the additional produce.

To the extent that collusion drives our results, we note that it departs from "textbook collusion" in an important manner. Economists typically view collusion as a way for firms to cooperate and maximize their collective profits, especially when firms can make transfers to one another (Tirole, 1988). Yet in our context, when we induced some vendors to break this collusive norm, profits went up for the entire market on average (column 3, Table 2). That is, there was unmet demand at the market level, and vendors who began selling peas and carrots were able to serve this demand and increase aggregate profits. Therefore, while collusive norms may have allowed vendors to sustain scales and prices that deviate from perfect competition, they are doing so in a way that leaves considerable aggregate profits on the table. This may be because simple heuristics such as, "do not sell exactly the same produce as your neighbor," are easier to enforce relative to more complex, profit-maximizing arrangements, especially when there are many market vendors.

On the other hand, the collusive norm was clearly flexible enough that our intervention had meaningful effects: quantities sold could change temporarily without generating a price war. The fact that our interventions benefited all vendors in the market – directly, in the case of carrots, and indirectly, in the case of peas – may also have facilitated a departure from the collusive equilibrium. Indeed, in the case of peas, the within-market sales that enabled established pea vendors to benefit from the subsidy as well may precisely be further evidence of collusion. However, it is possible that these kinds of more sophisticated mechanisms only work for a limited period of time and in the longer run collusion is easier with simple and rigid rules.

More generally, our evidence on the possibility of a sustained price premium, and limited competition in a market with many sellers, is important in how we think about policy attempts to benefit small sellers and consumers in developing country markets. The ease of colluding and/or inertial business practices may be reasons why interventions aimed at making markets more competitive have had at best limited success so far (Mitra et al., 2018; Banerjee et al., 2019; Busso and Galiani, 2019).

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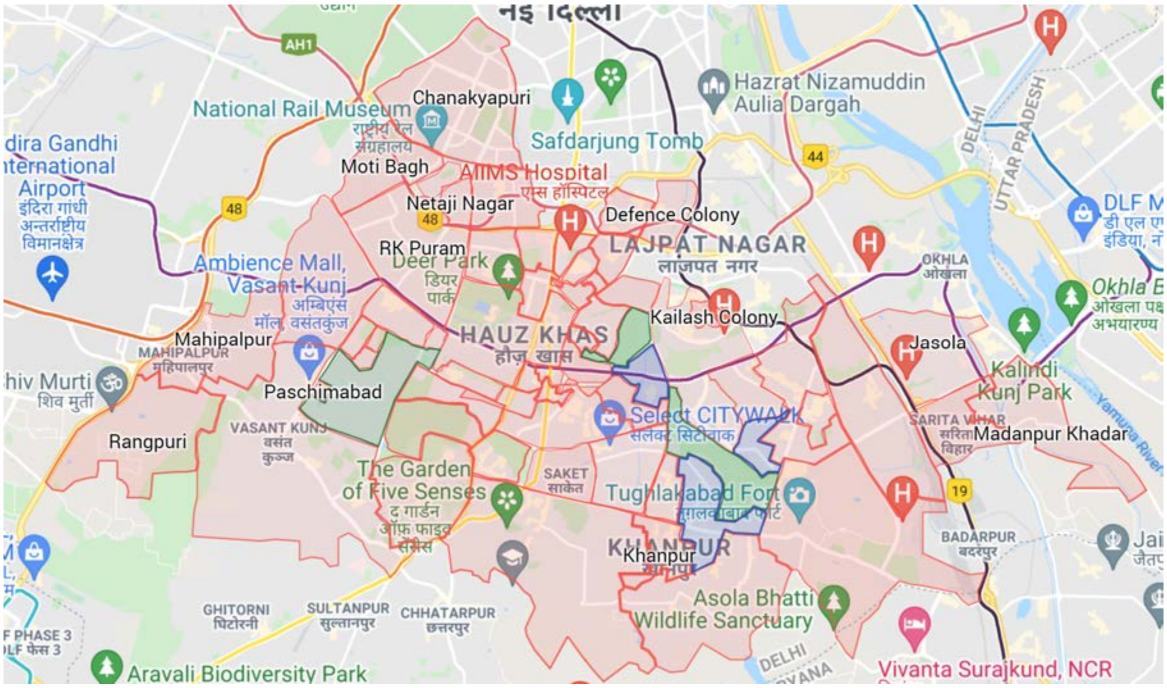
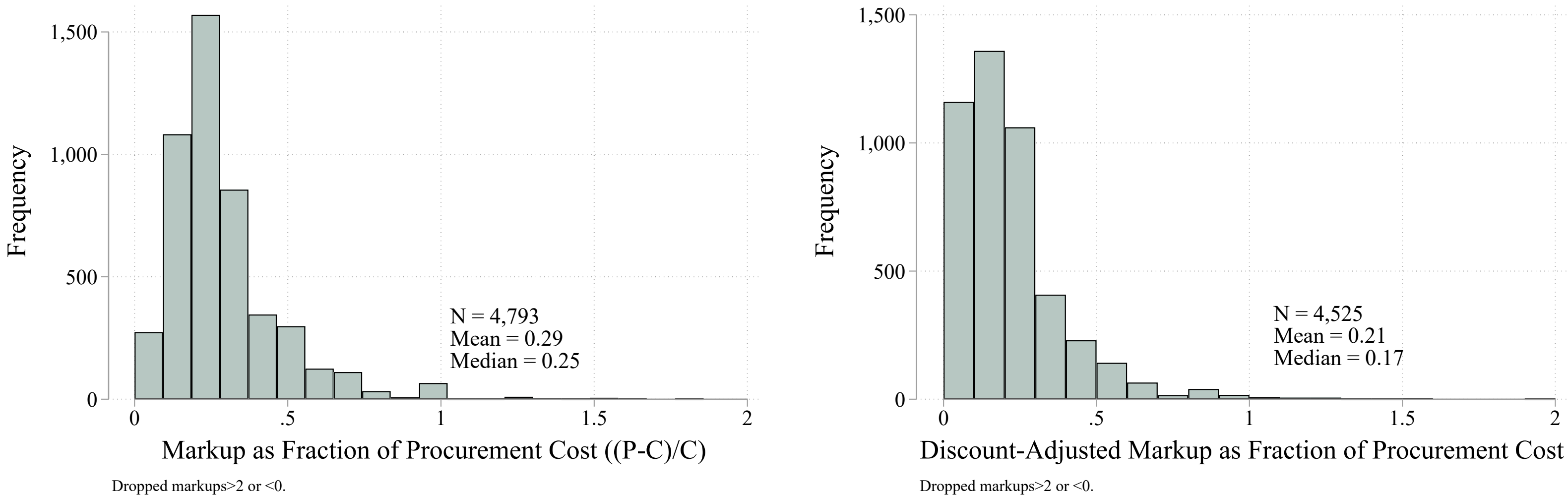
Appendix

Figure A1: Fruit Vendor Census Area



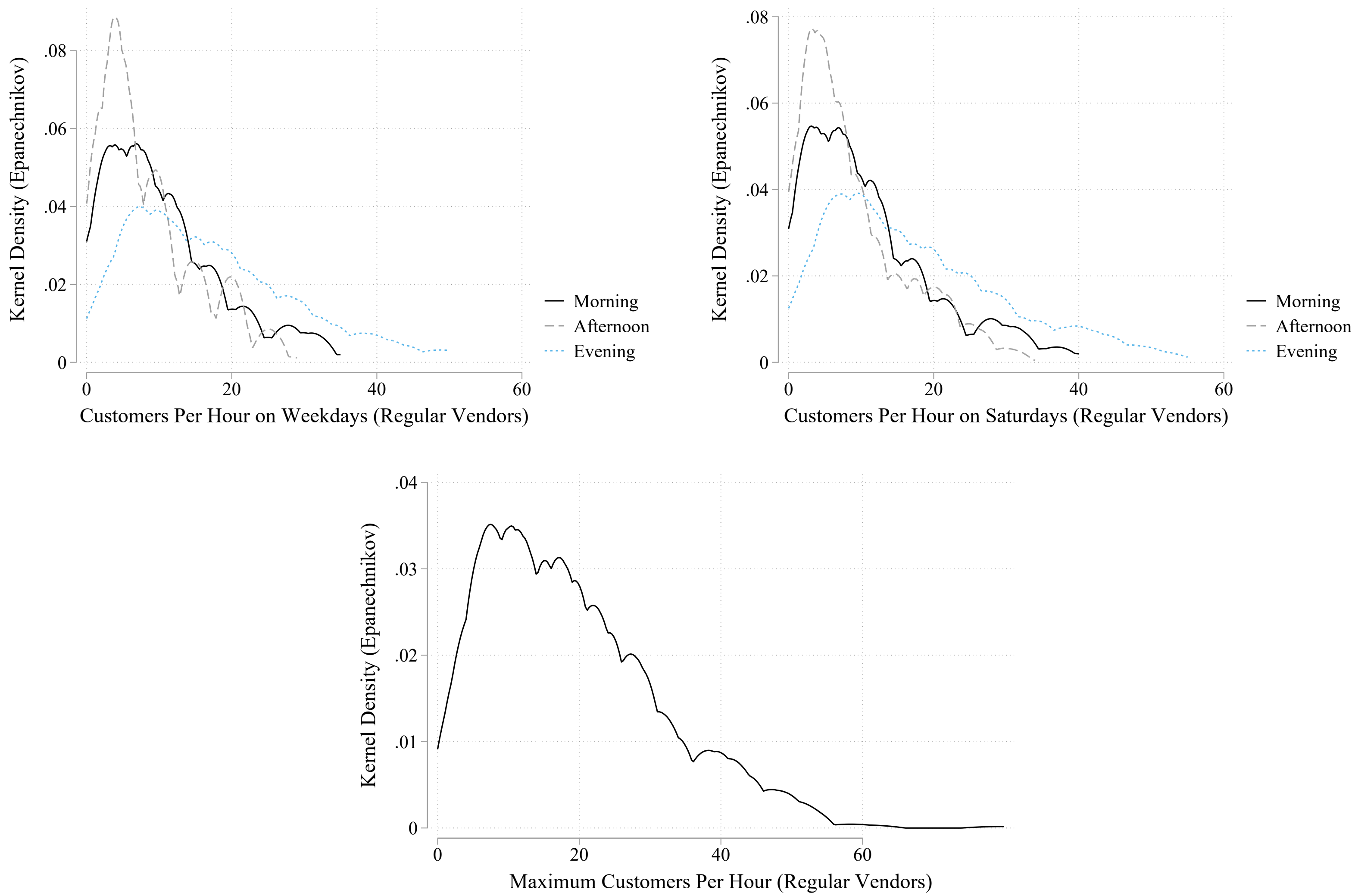
Notes: This figure shows the contiguous 135 square kilometer area of South Delhi covered by our vendor census. The red polygons cover 125 square kilometers and were successfully surveyed, the green polygons (Jawaharlal Nehru University, Hauz Khas Forest, and Jahanpanah Forest) are non-commercial areas and so were not surveyed, while the three blue polygons were erroneously missed.

Figure A2: The Distribution of Fruit-Level Markups



Notes: The figure shows the distribution of fruit-level markups as measured in the vendor census survey. In the left panel, the markup is measured as the stated selling price less the stated procurement cost, as a fraction of the stated procurement cost. In the right panel, we discount-adjust each markup by subtracting the vendor's stated typical discount (with the discount only measured at the vendor-level, rather than fruit-by-fruit). In both cases, we drop outliers above two or below zero (25 dropped from the left panel, 246 dropped from the right).

Figure A3: Many Vendors Are Not Very Busy



Notes: The top panel shows kernel densities of regular vendor answers to the question "what is the number of customers you serve during one hour of operations during each of these time periods on a [weekday/Saturday]?" In each case, the figure excludes any outlier answers at or above the 99th percentile. The bottom panel shows the kernel density of the maximum answer given to the six previous questions (weekday/Saturday-by-morning/afternoon/evening), as well as the equivalent questions for Sunday, which were only asked in the rare case that vendors said Sunday demand was different to Saturday demand.

Table A1: Descriptive Statistics for Intervention and Control Markets

	Charu Market (1)	Sarkar Bazar (2)	Alam Bazar (3)	Control markets (4)
Mean # vendors in census	45.0	73.0	85.0	85.8
Mean # vendors present per day	34.5	57.4	71.7	86.7
Mean profits per vendor	448.9	344.9	314.6	519.6
Mean # vegetables available per vendor	5.7	5.1	4.0	5.2
% of present vendors selling peas	62.9	59.9	51.8	61.0
% of present vendors selling carrots	65.1	52.2	39.1	54.1

Notes: This table presents summary statistics averaged for each intervention market in columns 1 - 3 and averaged over all control markets in column 4. All statistics are calculated using data from the pre-subsidy period. Each of the control markets is assigned equal weight in the reported mean. Profits are calculated by computing (amount of vegetable at the start of the day - amount left over at the end of the day)*anticipated sale price - (amount procured at the start of the day * procurement cost). On days where amount left over was not observed, we impute the vendor's average amount left over all days in which it was measured.

Table A2: Testing for Parallel Trends in the Pre-Subsidy Period

	Carrots				Peas			
	Prob. of selling (%)	Sale price (Rs.)	Wholesale qty. bought (kg)	Profit (Rs.)	Prob. of selling (%)	Sale price (Rs.)	Wholesale qty. bought (kg)	Profit (Rs.)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Carrots and Peas								
β_2: Treat	-0.05	-3.21	-1.51	-13.06	-0.08	-0.44	-3.92	-32.10
	[-0.248, 0.193]	[-7.535, 0.730]	[-3.286, 0.389]	[-27.041, 7.682]	[-0.367, 0.210]	[-5.135, 5.513]	[-8.004, -0.484]	[-59.564, 6.656]
	{ 0.700 }	{ 0.095 }	{ 0.130 }	{ 0.311 }	{ 0.513 }	{ 0.749 }	{ 0.046 }	{ 0.056 }
	⟨ 0.606 ⟩	⟨ 0.181 ⟩	⟨ 0.218 ⟩	⟨ 0.183 ⟩	⟨ 0.504 ⟩	⟨ 0.789 ⟩	⟨ 0.013 ⟩	⟨ 0.021 ⟩
β_3: Treat × Day	-0.00	0.08	0.04	0.17	0.00	0.06	0.19	-0.22
	[-0.012, 0.009]	[-0.290, 0.499]	[-0.073, 0.161]	[-1.566, 2.095]	[-0.006, 0.013]	[-0.252, 0.345]	[-0.133, 0.537]	[-3.594, 3.862]
	{ 0.984 }	{ 0.715 }	{ 0.444 }	{ 0.708 }	{ 0.586 }	{ 0.694 }	{ 0.642 }	{ 0.737 }
	⟨ 0.992 ⟩	⟨ 0.626 ⟩	⟨ 0.529 ⟩	⟨ 0.748 ⟩	⟨ 0.447 ⟩	⟨ 0.606 ⟩	⟨ 0.518 ⟩	⟨ 0.839 ⟩
Intervention market mean	0.49	27.88	3.40	24.95	0.57	41.75	5.71	44.50
N vendors	1591	1361	1591	1591	1591	1373	1591	1591
Observations	20040	10675	20040	20040	20040	12053	20040	20040
	Cost of wholesale purchases (Rs.)	Sales (Rs.)	Profits (Rs.)	# vegetables available				
Panel B: Aggregate								
β_2: Treat	-550.19	-689.20	-139.01	-0.40				
	[-1189.504, 3.171]	[-1348.365, -68.468]	[-368.186, 73.622]	[-2.712, 2.010]				
	{ 0.051 }	{ 0.042 }	{ 0.219 }	{ 0.625 }				
	⟨ 0.078 ⟩	⟨ 0.021 ⟩	⟨ 0.151 ⟩	⟨ 0.623 ⟩				
β_3: Treat × Day	13.02	12.88	-0.14	-0.01				
	[-9.307, 33.429]	[-14.460, 40.270]	[-10.147, 10.171]	[-0.072, 0.076]				
	{ 0.525 }	{ 0.607 }	{ 0.980 }	{ 0.366 }				
	⟨ 0.381 ⟩	⟨ 0.469 ⟩	⟨ 0.970 ⟩	⟨ 0.495 ⟩				
Intervention market mean	825.12	1167.30	342.18	4.73				
N vendors	1591	1591	1591	1591				
Observations	20040	20040	20040	20040				

Notes: This table estimates the following specification: $y_{it} = \alpha + \beta_1 Day_t + \beta_2 Treat_m + \beta_3 Day_t \times Treat_m + \varepsilon_{imt}$ on our sample during the pre-subsidy period. Coefficients for Day not shown. 95% wild bootstrap confidence intervals are in [], wild bootstrap p-value is in {}, and Fisher permutation p-value is in ⟨⟩. In Panel A, outcomes are specific to peas or carrots. The outcome in columns 1 and 5 is whether the vendor sells carrots or peas on the given day, the outcome in columns 2 and 6 measure the vendor's anticipated sale price for the relevant vegetable, the outcome in columns 3 and 7 measure the wholesale quantity procured of the relevant vegetable, and the outcome in columns 4 and 8 measure the daily profits accrued from the relevant vegetables. Profits are calculated by computing (amount of vegetable at the start of the day - amount left over at the end of the day)*anticipated sale price - (amount procured at the start of the day * procurement cost). On days where amount left over was not observed, we impute the vendor's average amount left over all days in which it was measured. Our measure of profit does not include the subsidy vendors received as part of our intervention. In Panel B the outcomes correspond to aggregate measures. The outcome in column 1 is the total cost of wholesale purchases on a given day, the outcome in column 2 is the vendor's total revenues on a given day accruing from all produce, the outcome in column 3 is the daily profits accrued from all produce, and the outcome in column 4 is the number of distinct types of vegetables a vendor has available on a given day.

Table A3: Subsidy Impacts on Carrots: By Pre-Period Carrot Sales

	Sold carrots < 8 days				Sold carrots ≥ 8 days			
	Prob. of selling (%)	Sale price (Rs.)	Wholesale qty. bought (kg)	Profit (Rs.)	Prob. of selling (%)	Sale price (Rs.)	Wholesale qty. bought (kg)	Profit (Rs.)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_3: Treat	-0.03	0.14	-0.88	-7.44	-0.01	-3.06	-1.32	-13.12
	[-0.098, 0.038]	[-10.724, 10.784]	[-2.328, 0.046]	[-20.065, 9.296]	[-0.144, 0.148]	[-9.278, 2.120]	[-5.423, 1.905]	[-40.470, 15.024]
	{ 0.218 }	{ 0.942 }	{ 0.053 }	{ 0.094 }	{ 0.952 }	{ 0.070 }	{ 0.199 }	{ 0.256 }
	⟨ 0.439 ⟩	⟨ 0.948 ⟩	⟨ 0.007 ⟩	⟨ 0.039 ⟩	⟨ 0.929 ⟩	⟨ 0.086 ⟩	⟨ 0.268 ⟩	⟨ 0.212 ⟩
γ_1: Treat x During	0.69	-1.87	5.85	44.58	0.45	0.16	6.00	44.78
	[0.601, 0.770]	[-4.960, 2.186]	[4.734, 6.605]	[30.014, 55.950]	[0.251, 0.689]	[-3.699, 3.803]	[3.787, 8.638]	[17.976, 67.620]
	{ <0.001 }	{ 0.548 }	{ <0.001 }	{ 0.001 }	{ 0.010 }	{ 0.782 }	{ 0.004 }	{ 0.016 }
	⟨ <0.001 ⟩	⟨ 0.361 ⟩	⟨ <0.001 ⟩	⟨ 0.003 ⟩	⟨ <0.001 ⟩	⟨ 0.865 ⟩	⟨ <0.001 ⟩	⟨ 0.003 ⟩
γ_2: Treat x After	0.12	-1.59	1.85	11.21	0.08	-2.11	1.86	6.94
	[0.030, 0.174]	[-9.009, 5.209]	[0.644, 2.619]	[2.452, 20.951]	[-0.222, 0.352]	[-10.388, 7.158]	[-1.013, 5.157]	[-38.548, 45.607]
	{ 0.025 }	{ 0.275 }	{ 0.013 }	{ 0.032 }	{ 0.430 }	{ 0.208 }	{ 0.101 }	{ 0.397 }
	⟨ 0.049 ⟩	⟨ 0.467 ⟩	⟨ 0.012 ⟩	⟨ 0.004 ⟩	⟨ 0.483 ⟩	⟨ 0.240 ⟩	⟨ 0.312 ⟩	⟨ 0.482 ⟩
Pre-subsidy intervention market mean	0.15	27.92	0.84	6.74	0.79	27.91	5.69	41.66
Wild Bootstrap p-value: $\gamma_1 = \gamma_2$	<0.001	0.939	<0.001	<0.001	0.010	0.178	0.012	0.041
Fisher p-value: $\gamma_1 = \gamma_2$	<0.001	0.942	<0.001	0.002	0.002	0.166	<0.001	<0.001
N vendors	629	517	629	629	1002	953	1002	1002
Observations	22045	4408	22045	22044	33173	20665	33173	33169

Notes: This table estimates specification 1 on our full sample. Coefficients for During and Post not shown. 95% wild bootstrap confidence intervals are in [], wild bootstrap p-value is in {}, and Fisher permutation p-value is in ⟨⟩. Columns 1 - 4 present outcomes for vendors who sold carrots on less than 8 days during the pre-subsidy period (analogous to the pea subsidy eligibility criterion) and 5 - 8 present outcomes for vendors who sold carrots on 8 or more days during the pre-subsidy period. The outcome in columns 1 and 5 is whether the vendor sells carrots on the given day, the outcome in columns 2 and 6 measure the vendor's anticipated sale price for carrots, the outcome in columns 3 and 7 measure the wholesale quantity of carrots procured, and the outcome in columns 4 and 8 measure the daily profits accrued from carrots. Profits are calculated by computing (amount of carrots at the start of the day - amount left over at the end of the day)*anticipated sale price - (amount procured at the start of the day * procurement cost). On days where amount left over was not observed, we impute the vendor's average amount left over all days in which it was measured. Our measure of profit does not include the subsidy vendors received as part of our intervention.