A comment on Sell Low and Buy High: Arbitrage and Local Price Effects in Kenyan Markets by Burke, Bergquist, and Miguel

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Abstract

This paper replicates the results of Burke et al., 2018b examining the micro-credit on the buying and selling behaviours of small-scale farmers in Kenya. By partnering with the One Acre Fund, the original study facilitated credit access to these farmers, influencing their market behaviours notably during post-harvest periods. Our replication utilises the same dataset and statistical methodologies but rewrites the code in Python instead of STATA. We are able to confirm the original findings with only minor discrepancies, suggesting these could be due to rounding errors. Access to micro-credit does have a statistically significant impact on the inventory levels and net revenue of treated farmers as they shift their sales to later in the season when prices are higher. Further, we find indicative evidence of positive spill-over effects for the non-treated population, though statistically insignificant.

KEYWORDS: replication; storage; arbitrage; microcredit; credit constraints; agriculture

JEL CODES: D21, D51, G21, O13, O16, Q12

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1 Introduction

In this replication report, we are replicating Burke et al., 2018b. The paper focuses on local grain markets in Kenya and how small-scale farmers are observed to be selling low and buying high due to credit restrictions. The authors partnered with the One Acre Fund (OAF) in Kenya to provide credit to randomly selected small-scale farmers in 2013 and 2014 and further saturate the different local markets randomly by only enrolling either 40% or 80% of the farmers OAF worked in the study with and only provide credit to around 58% of the participants[1]. The study claims that providing farmers with timely access to credit enables them to purchase more maize immediately post-harvest when prices are lower and sell less, reversing this behaviour during the period of higher prices several months later. This strategic shift in buying and selling behaviour due to the credit intervention significantly increases farmer revenues. *"We find that farmers offered this harvest-time loan sold significantly less and purchased significantly more maize immediately following harvest and that this pattern reversed during the period of higher prices 6-9 months later. This change in their marketing behaviour resulted in a statistically significant increase in revenues"* (p. 2-3). Further, they find that the introduction of credit to a selected number of farmers stabilises the prices throughout the year as *"increased grain storage at the market level (induced by the credit intervention) led to significantly higher prices immediately after harvest and to lower (albeit not significantly so) prices during the lean season"* (p. 3).

We have chosen to reproduce these main findings of the paper, looking at the effects on inventory (table 2), net revenue (table 3), and HH consumption (table 4). I.e., do farmers that receive credit change their behaviour when they sell their grain, inventory effects, does this affect the net revenue, and does this affect the household consumption. We use the available replication data through Burke et al., 2018a. Additionally, we examine the aforementioned effects, taking into account

[1]In the first year 2/3 of the enrolled population making the while in the second year 1/2 of the enrolled received a loan offer.

the treatment intensity (table 7), i.e. what is the effect of offering more or less farmers access to credit. We also examine the effect on prices by looking at the net sales and effective prices (table 5) and the market prices as a function of saturation (table 6)

Though we do find some discrepancies in the data and the STATA code provided, see section 2, we are able to reproduce the results from the paper, with only very slight deviations in some results – table 3 specifically. We find that the overall effect in years 1 and 2 are ~ 1 Ksh smaller whilst the total effect is ~ 1 Ksh higher, deviations of -0.005%, -0.001% and 0.003% respectively.

2 Reproducibility

As mentioned in section 1, we will now turn our attention to the reproduction of the paper and reproduce the main finding presented in the Burke et al., 2018b tables 2 through 7 by rewriting the code and running the necessary regressions in Python.

For the replication, we are using the 1.2 version of Burke et al., 2018a accessible through the Havard Dataverse published on April 9, 2019. However, the only difference between this and the original 1.0 version published on December 23, 2018, is the addition of a citation in the metadata.

We have noticed the aforementioned data does not align completely with the data used in the STATA code provided by the same source. Specifically, we see the STATA code, from the same source, rename columns in the *baseline.dta* to include the suffix *_base*. However, 2 of the columns have already been renamed.[2] This does not seem to affect the results; however, it indicates that the authors used a slightly different dataset, making it impossible to say if anything else has been altered. Additionally, there seem to be some redundancies in the STATA code[3] however,

[2] Already renamed columns are 'delta_base', 'businessprofitmonth_base'.

[3] We, e.g., find in lines 172-174 (and 5801-5803);

```
drop if merge_base ==2;
gen in_sample_Y2 = (merge_base ==3);
gen newin13=(merge_base==2)
```

As rows with merge_base ==2 are dropped, there will be no rows with the newin13 bool being true. This specific bool is used in line 241 to filter the data but has no effect.

these solely seem to have an impact on performance.

Furthermore, we note that table 8 is *not* created through STATA, though the .do file does not specify this[4]. Instead, its calculation method is laid out in the full paper's Appendix M.I, included here as appendix B.

Lastly, we believe that Burke et al., 2018b has made some rounding errors in the p-values. Using equations (7) and (6), we can calculate the Student's-t p-value of High in the original papers table 6 (and our table 6) from the given standard deviation and estimated value

$$\text{p-value} = 2 \cdot \left(1 - \int_{-\infty}^{\left|\frac{4.41}{2.09}\right|} \frac{\Gamma\left(\frac{16+1}{2}\right)}{\sqrt{16\pi}\Gamma\left(\frac{16}{2}\right)} \left(1 + \frac{x^2}{16}\right)^{-\frac{16+1}{2}} dx \right) = 0.05095 \qquad (1)$$

The authors reported that the value of 0.052 is correct with 15 degrees of freedom, but the data in question has 17 clusters, resulting in 16 degrees of freedom – following the convention $\nu = G - 1$, where G is the number of clusters. This is not off by a huge margin, but it is still slightly off, and we have noticed this for several other values.

2.1 Regression models

2.1.1 Individual effects: For tables 2, 3, 4, and 5, we explore the effects on an individual level through the following regressions formula for the overall effect:

$$Y_{ijry} = \alpha + \beta T_{jy} + \eta_{ry} + \delta_t + \gamma_s + \varepsilon_{ijry} \qquad (2)$$

Where Y is the dependent variable of interest $\in$ [inventory, net revenue, log total household consumption], for individual i in group j, for round $r \in (1, 2, 3)$ in year y (also including the pooled specification). T indicates whether or not individual i was offered a loan in year y while the variables η_{ry} and δ_t are the year-round fixed effects, interview dates, as every round of surveying was conducted over three months. Lastly, γ_s are stratification dummies.

[4]Other figures are listed under *List of Tables and Figures not created using STATA*, but not table 8

The value of interest here is β, which estimates the ITT and can be interpreted as the average effect of being *offered* the loan product across follow-up rounds and assumes a constant effect throughout the year. If the credit allows farmers to properly shift their sales to periods with higher prices, we would expect $\beta > 0$ for all estimations in our analysis.

To further understand the intra-year variation, we also estimate:

$$Y_{ijry} = \alpha + \sum_{r=1}^{3} \beta_r T_{jy} + \eta_{ry} + \delta_t + \gamma_s + \varepsilon_{ijry} \tag{3}$$

Where we, for each round, estimate the β_r as our value of interest. The expected behaviour would be that farmers who are offered credit access would shift their sales to later in the season; the signs of β_1 and β_3 are therefore expected to be opposite when looking at inventory levels (where we expect $\beta_1 > 0$), net revenue (where we expect $\beta_1 < 0$) and net sales (where we expect $\beta_1 > 0$). For the overall HH consumption, we would expect it to increase across all rounds as the credit loosens their budget constraints, allowing for a smoother consumption and increased net revenue, i.e., $\beta_r > 0 \; \forall \; r \in [1, 2, 3]$.

2.1.2 Market effects:

For table 6, we move on to the effects on the local grain prices with the main focus of the original article by estimating the effects of the market price of maize specifically as a function of treatment intensity with the following model

$$p_{msty} = \alpha + \beta H_s + \beta_2 month_t + \beta_3 (H_s \times month_t) + \varepsilon_{msty} \tag{4}$$

Where p is the price of maize in market m in sublocation s in month t in year y. H_s is a boolean variable indicating that sublocation s was a high- or low-intensity sublocation, and $month_t$ is a monthly trend since the last harvest such that 0 is November.

The values of interest are β_1, β_2 and β_3 – the expected effect is that prices, in general, are higher in the beginning in highly treated areas as more farmers with access to loans can shift their sales to later in the season driving down supply and thus increasing prices immediately after harvest. The more time passes. However, the more grain will come to the market, driving down prices over time, i.e. the expected values would be $\beta_1 > 0$ and $\beta_3 < 0$. For β_2, we would expect $\beta_2 > 0$, i.e., prices still increase over time. If the high saturation can fully offset the increasing prices, we would expect $\beta_2 = \beta_3$.

2.1.3 Treatment density effects on individual levels: In table 7, we examine the effects of density on the individual level. We estimate equations (2) again but include a dummy of high density and the interaction term between the two treatments and high intensity. The regression, therefore, is:

$$Y_{ijry} = \alpha + \beta_1 T_{jy} + \beta_2 H_s + \beta_3 (T \times H) + \eta_{ry} + \delta_t + \gamma_s + \varepsilon_{ijry} \tag{5}$$

Were all variable are as explained previously for equations (2) and (4).

The values of interest are β_1, β_2, and β_3, to identify the individual effect. The expected values assuming farmers offered loans shift their behaviour imply that they have higher inventory, net revenue and consumption, i.e. $\beta_1 > 0$. If prices increase, we would expect control farmers in high-saturation areas to do better than in low-density areas as the increased prices right after harvest make them sell slightly less and at a higher price, hence $\beta_2 > 0$. For β_3, we would expect the reverse effect, $\beta_3 < 0$, i.e., treated farmers in high-density areas do worse than treated farmers in low-density areas.

2.2 P-values and Robustness Checks

We noted that all p-values reported by Burke et al., 2018b are calculated from the t-statistic and not the z-statistic reported by default in our Python models. We, therefore, recalculate all the p-values using the Student's-t distribution with the number of no. clusters − 1 as the degrees of freedom, i.e.

$$\text{p-value} = 2 \cdot \left(1 - \int_{-\infty}^{|t|} \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\,\Gamma\left(\frac{\nu}{2}\right)} \left(1 + \frac{x^2}{\nu}\right)^{-\frac{\nu+1}{2}} dx\right) \tag{6}$$

Where ν is the degrees of freedom, Γ is the gamma function and t is the t-statistic defined as

$$t_i = \frac{\hat{\beta}_i - \mu_{0_i}}{\sigma_{\hat{\beta}_i}} \tag{7}$$

Where $\hat{\beta}_i$ is the estimated coefficient, μ_0 is the null hypothesis – for all our estimates, this is 0 – and $\sigma_{\hat{\beta}_i}$ is the standard deviation of the coefficient.

Though table 1 has enough individual observations and tables 2 through 5 enough clusters that one usually would report the z-statistic along with p-values from the normal distribution, we still report values p-values using the Student's-t distribution for consistency across the paper and to exactly replicate the results from Burke et al., 2018b.

2.2.1 Family-Wise Error Rate

For tables 2 through 5, we report the Family-Wise Error Rates as in the original paper. These are calculated with statsmodels.stats.multitest.multipletests using the method Benjamini/Hochberg (non-negative) (fdr_bh). The family of outcomes is inventories, net revenues, consumption, and effective prices for the overall findings, whilst the family by round p-values are based on the family solely containing inventories, net revenues, and consumption.

2.2.2 Wild Cluster Bootstrap-t (WCB-t)

For tables 6 and 7, we check the robustness of our results by conducting a wild cluster bootstrap-t procedure. Burke et al., 2018b uses the cgmwildboot, an implementation of the wild bootstrap-t procedure described by Cameron et al., 2008 and implemented in STATA by Judson Caskey, n.d. However, as this function is *not* an official STATA function thus, documentation for it is limited. Using Cameron et al., 2008, we have attempted to implement our own cgmwildboot in Python (defined separately in proj03.py), where we for each bootstrap regression estimate

$$\hat{\mathbf{y}}^* = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{8}$$

Where $\mathbf{X}$ is the matrix of independent variables, $\boldsymbol{\beta}$ is the coefficients, and $\boldsymbol{\varepsilon}$ is the error term. The dependent variable, $\hat{\mathbf{y}}^*$, is the one we vary over in each bootstrap iteration and is calculated as

$$\hat{\mathbf{y}}^* = \hat{\mathbf{y}} + \hat{\boldsymbol{\varepsilon}}^* \tag{9}$$

Where $\hat{\mathbf{y}}$ is the predicted value of the dependent variable in the original model and $\hat{\boldsymbol{\varepsilon}}^*$ is calculated as the residuals from the original model, $\hat{\boldsymbol{\varepsilon}}$, multiplied by a cluster-randomised Rademacher weights i.e. with probability 0.5 $\hat{\boldsymbol{\varepsilon}}^* = \hat{\boldsymbol{\varepsilon}}$ and with probability 0.5 $\hat{\boldsymbol{\varepsilon}}^* = -\hat{\boldsymbol{\varepsilon}}$.

Using our bootstrap estimated $\hat{\boldsymbol{\beta}}^*$ we can calculate the Wald statistic for each estimatiation as

$$w^*_{i,b} = \frac{\hat{\beta}^*_{i,b} - \hat{\beta}_i}{\sigma_{\hat{\beta}^*_{i,b}}} \tag{10}$$

Where $\hat{\beta}^*_{i,b}$ estimated coefficient i in the bth iteration, $\hat{\beta}_i$ is the original estimated coefficient and $\sigma_{\hat{\beta}_{i,b}}$ is the standard deviation of the bth bootstrap estimate. This we compare with the Wald statistic of the original model

$$w_i = \frac{\hat{\beta}^*_i - \mu_0}{\sigma_{\hat{\beta}^*_i}} \tag{11}$$

Where μ_0 is the null hypothesis. Lastly, we estimate the two-sided p-value using the empirical distribution as

$$\text{p-value}_i = \frac{1}{B}\sum_{b=0}^{B} I(|w^*_{i,b}| > |w_i) \tag{12}$$

Where I is the indicator function.

2.3 Results

Our replication analysis confirms the primary findings of Burke et al., 2018b, focusing on the impact of credit access on the buying and selling behaviours of small-scale farmers in Kenya. Using Python, we have successfully reproduced the original study's results on inventory effects, net revenue, household consumption, and market prices, with only negligible deviations.

2.3.1 Inventory Effects: Consistent with the original findings, our results show that farmers with access to credit were able to maintain higher inventory levels post-harvest (tables 2 and 7). This effect was statistically significant across all rounds and both years of the study.

2.3.2 Net Revenue and Sales: We observed a significant increase in overall net revenue among farmers who received credit, primarily driven by higher revenues later in the year (table 3). However, this effect is not significant for the first year. Although our replication found a minimal difference (approximately 1 Ksh) in revenue outcomes compared to the original study, these differences were economically insignificant, representing mere decimal point variations in percentage terms (-0.005% in year 1, -0.001% in year 2, and 0.003% in overall). We cannot say if this is due to some changes in the data described in 2, as we have not had access to STATA and have been unable to run the .do file using the edited data file. Table 5 provides an explanation for the increased revenue overall as we find a statistically significant effect on both effective prices and sales behaviour for farmers with access to credit. We find that farmers with access to credit sell less right after harvest and then increase their sales as time since harvest passes, making their effective purchase price lower and their effective sales price higher. These effects are significant at the 5% level, and we have gotten identical results as Burke et al., 2018b.

2.3.3 Household Consumption: Our analysis supports the original study's conclusion that the availability of microcredit seems to have a positive impact on household consumption; however, this is not statistically significant at the 5% level (table 4), where we were able to get identical results to the original study.

2.3.4 Saturation Effects:

Our replication also finds that high saturation affects the market prices (table 6). However, as Burke et al., 2018b, we only find the effect to be significant at the 5% level, though there are slight differences in p-values as described in 2, as our estimates and clustered standard deviations are equivalent.

On the individual level, we find no statistically significant differences between the high and low treated areas, only that treated farmers have a higher net revenue and a higher inventory. With that said, however, the numbers do indicate - though not statistically significant so - that control farmers have slightly higher inventory and net revenues in highly saturated areas $\hat{\beta}_{hi} > 0$ whilst farmers offered credit have lower inventory and net revenues than their peers in the low saturated areas, $\hat{\beta}_{T\times hi} < 0$ in line with the findings of Burke et al., 2018b.

As shown in A figures 1, the bootstrapped estimations follow at Student's-t distribution, meaning the standard reported t-values from table 6 are valid. For table 7, we in figure 2 show that the especially inventory and net revenue do not seem to be the Student's-t distributed, and thus, the bootstrapped p-values are the most appropriate.

Exactly the bootstrapped p-values are the only major differences in our estimated values in tables 6 and 7 are our estimated bootstrap p-values. We run our WCB-t procedure 5000 times iterations using the numpy seed 5005 whilst Burke et al., 2018b only runs the procedure 1000 times using the STATA seed 894561. As seeds are different between the systems, we would not expect to get identical values; however, though different, there is no impact on whether or not any estimate is significant.

2.3.5 Spill-over effects:

Underlying assumptions always can be argued, but taking all point estimates as given, we in table 8 present the estimated welfare gains across the entire population using the assumptions presented in appendix B. These results show that while direct gains are lower in high-saturation areas, the total welfare gains are higher than those in low-saturation areas as the indirect spill-over effects accrue to many untreated individuals.

3 Conclusion

Our paper successfully replicated the main findings of Burke et al., 2018b, utilising Python to achieve comparable results. Our replication shows the robustness of the original study's conclusions regarding the positive effects of credit access on economic behaviours and outcomes of small-scale farmers in Kenya. Providing credit enables farmers to manage their resources more effectively, as evidenced by their ability to maintain higher inventory levels and achieve greater net revenue. This is particularly evident in their ability to sell less immediately post-harvest and sell more at higher prices later, optimising their financial outcomes. Further, we find indications of spill-over effects where control farmers also benefit from this, though not significant.

While some statistical outputs differed slightly due to methodological variations, such as the number of bootstrap iterations and choice of seed, this did not affect the significance. We find some peculiarities in the estimated p-values that lead us to believe that the original authors might have made some rounding errors in their data. However, this does not affect the conclusion or validity of the paper. What affects the validity of the non-bootstrapped p-values is the non-Student's-t distribution of bootstrap estimates shown in figure 2, which invalidates the p-values from the standard clustered distribution.

References

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4 Tables

Table 1. **Summary statistics and balance among baseline covariates.** Balance table for the Y1 sample. The first two columns give the means in each treatment arm. The third column gives the total number of observations across the two groups. The last two columns give differences in means normalised by the standard deviation in the control group, with the corresponding p-value on the test of equality.

Baseline characteristic	Treat	Control	Obs	Std diff	P-val
Male	0.296	0.334	1589	-0.081	0.107
Number of adults	3.004	3.196	1510	-0.092	0.060
Children in school	2.998	3.072	1589	-0.039	0.457
Finished primary school	0.718	0.772	1490	-0.128	0.021
Finished secondary school	0.253	0.270	1490	-0.039	0.458
Total cropland (acres)	2.441	2.398	1512	0.013	0.792
Number of rooms in household	3.073	3.252	1511	-0.055	0.170
Total school fees	27239.693	29813.631	1589	-0.064	0.182
Average monthly consumption (Ksh)	14970.862	15371.378	1437	-0.033	0.554
Average monthly consumption/capita (log)	7.975	7.963	1434	0.019	0.721
Total cash savings (Ksh)	5157.396	8021.499	1572	-0.095	0.013
Total cash savings (trim)	4731.623	5389.836	1572	-0.046	0.327
Has bank savings acct	0.419	0.425	1589	-0.012	0.815
Taken bank loan	0.079	0.083	1589	-0.018	0.728
Taken informal loan	0.244	0.249	1589	-0.011	0.836
Liquid wealth (Ksh)	93878.938	97280.922	1491	-0.032	0.545
Off-farm wages (Ksh)	3916.817	3797.480	1589	0.009	0.849
Business profit (Ksh)	2302.588	1801.685	1589	0.083	0.322
Avg %Δ price Sep-Jun	133.495	133.178	1504	0.004	0.939
Expect %Δ price Sep12-Jun13	124.680	117.255	1510	0.141	0.155
2011 LR harvest (bags)	9.364	9.025	1511	0.023	0.671
Net revenue 2011 (Ksh)	-3303.691	-4088.622	1428	0.031	0.749
Net seller 2011	0.324	0.303	1428	0.047	0.394
Autarkic 2011	0.068	0.060	1589	0.035	0.511
% maize lost 2011	0.016	0.013	1428	0.033	0.573
2012 LR harvest (bags)	11.181	11.030	1484	0.019	0.740
Calculated interest correctly	0.715	0.730	1580	-0.035	0.504
Digit span recall	4.568	4.576	1504	-0.007	0.891
Maize giver	0.261	0.261	1589	-0.001	0.985

Notes: "Total school fees" are the total school fees paid by the household in the past 12 months. "Taken bank loan" is whether anyone in the household has taken any loans from a commercial bank or commercial lender in the past 12 months. 'Taken informal loan" is whether anyone in the household has taken any loans from a moneylender or someone else outside the household in the past 12 months."Liquid wealth" is the sum of cash savings and assets that could be easily sold (e.g. livestock). "Off-farm wages" is the total amount earned by anyone in the household who worked in a job for cash in the past month. "Business profits" are the total profits earned from all businesses run by anyone in the household. "Avg %Δ price Sep-Jun" is the percentage difference between the (self-reported) average market price for maize in September and June over the past five years. "Net revenue," "net seller," and "autarkic" refer to the household's maize marketing position. "Maize giver" is whether the household reported giving away more maize in gifts than it received over the previous 3 months.

Table 2. **Inventory Effects, individual level.** The dependent variable is inventories, as measured by the number of 90kg bags of maize held by the household at the time of the survey. "Treat" is an indicator of being in a treatment group. "Treat - R "x"" is an interaction between an indicator for being in a treatment group and an indicator for being in Round "x." Regressions include round-year fixed effects, strata dummies, and controls for survey dates, with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Standard p-values are clustered by group, and FWER p-values are calculated as specified in section 2.2.1.

	Dependent variable: Inventory Trim					
	Y1		Y2		Pooled	
	(1) Overall	(2) By rd	(3) Overall	(4) By rd	(5) Overall	(6) By rd
Treat	0.574***		0.546***		0.565***	
	(0.140)		(0.129)		(0.097)	
Treat - R1		0.872***		1.242***		1.050***
		(0.276)		(0.235)		(0.184)
Treat - R2		0.753***		0.304*		0.546***
		(0.171)		(0.166)		(0.120)
Treat - R3		0.111		0.082		0.094
		(0.083)		(0.344)		(0.162)
Observations	3836	3836	2944	2944	6780	6780
R^2	0.365	0.368	0.098	0.215	0.144	0.329
Mean DV	3.021	3.021	1.959	1.959	2.56	2.56
SD DV	3.726	3.726	3.089	3.089	3.503	3.503
P-Val Treat	<0.001		<0.001		<0.001	
P-Val Treat FWER	<0.001		<0.001		<0.001	
P-Val Treat - R1		0.002		<0.001		<0.001
P-Val Treat - R1 FWER		0.004		<0.001		<0.001
P-Val Treat - R2		<0.001		0.068		<0.001
P-Val Treat - R2 FWER		<0.001		0.173		<0.001
P-Val Treat - R3		0.183		0.812		0.561
P-Val Treat - R3 FWER		0.33		0.913		0.631

Notes: Significant at the ***[1%] **[5%] *[10%] level.

Table 3. **Net revenue effects, individual level.** The dependent variable is net revenues, as measured by the value (in Ksh) of maize sales minus the value of maize purchases that round. The exchange rate during the study period ranged from 80 to 90 Kenyan shillings per USD. "Treat" is an indicator of being in a treatment group. "Treat - R "x"" is an interaction between an indicator for being in a treatment group and an indicator for being in Round "x." Regressions include round-year fixed effects, strata dummies, and controls for survey dates, with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Standard and Family-Wise Error Rate (FWER) p-values are presented in the notes for effective prices; the latter are calculated as specified in 2.2.1.

	Dependent variable: Net Revenue Trim					
	Y1		Y2		Pooled	
	(1) Overall	(2) By rd	(3) Overall	(4) By rd	(5) Overall	(6) By rd
Treat	263.790		854.114***		531.358***	
	(255.661)		(303.802)		(196.315)	
Treat - R1		-1164.574***		16.478		-613.581**
		(322.956)		(444.957)		(271.653)
Treat - R2		509.851		1994.923***		1187.967***
		(446.928)		(503.696)		(337.460)
Treat - R3		1370.344***		565.438		998.665***
		(412.602)		(403.307)		(291.103)
Observations	3795	3795	2935	2935	6730	6730
R^2	0.025	0.038	0.074	0.079	0.107	0.119
Mean DV	485.812	485.812	-2997.862	-2997.862	-1033.442	-1033.442
SD DV	6212.781	6212.781	6545.626	6545.626	6590.086	6590.086
P-Val Treat	0.303		0.006		0.007	
P-Val Treat FWER	0.379		0.01		0.012	
P-Val Treat - R1		<0.001		0.971		0.024
P-Val Treat - R1 FWER		0.002		0.971		0.044
P-Val Treat - R2		0.255		<0.001		<0.001
P-Val Treat - R2 FWER		0.383		<0.001		0.001
P-Val Treat - R3		0.001		0.163		0.001
P-Val Treat - R3 FWER		0.003		0.259		0.001

Notes: Significant at the ***[1%] **[5%] *[10%] level.

Table 4. HH consumption (log) effects, individual level. The dependent variable is log HH consumption (measured in logged Ksh), aggregated from a detailed 30-day recall consumption module. "Treat" is an indicator of being in a treatment group. "Treat - R "x"" is an interaction between an indicator for being in a treatment group and an indicator for being in Round "x." Regressions include round-year fixed effects, strata dummies, and controls for survey dates, with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Standard and Family-Wise Error Rate (FWER) p-values are presented in the notes for effective prices; the latter are calculated as specified in 2.2.1.

	Dependent variable: Log Total HH Consumption Trim					
	Y1		Y2		Pooled	
	(1) Overall	(2) By rd	(3) Overall	(4) By rd	(5) Overall	(6) By rd
Treat	0.012		0.064*		0.036	
	(0.030)		(0.036)		(0.023)	
Treat - R1		-0.033		0.064		0.013
		(0.047)		(0.047)		(0.033)
Treat - R2		0.028		0.076*		0.049*
		(0.039)		(0.043)		(0.029)
Treat - R3		0.038		0.052		0.044
		(0.042)		(0.047)		(0.031)
Observations	3792	3792	2944	2944	6736	6736
R^2	0.026	0.027	0.051	0.053	0.055	0.056
Mean DV	9.477	9.477	9.653	9.653	9.554	9.554
SD DV	0.621	0.621	0.652	0.652	0.64	0.64
P-Val Treat	0.683		0.082		0.127	
P-Val Treat FWER	0.683		0.103		0.127	
P-Val Treat - R1		0.487		0.173		0.687
P-Val Treat - R1 FWER		0.487		0.259		0.687
P-Val Treat - R2		0.481		0.077		0.089
P-Val Treat - R2 FWER		0.487		0.173		0.133
P-Val Treat - R3		0.365		0.272		0.164
P-Val Treat - R3 FWER		0.469		0.349		0.211

Notes: Significant at the ***[1%] **[5%] *[10%] level.

Table 5. Net sales and effective prices, individual level. The dependent variable in Columns 1-2 is net sales (quantity sold minus quantity purchased, measured in 90kg bags of maize) that round. Columns 1-2 include round-year fixed effects, strata dummies, and controls for survey date, with errors clustered at the group level. The dependent variable in Column 3 is "Effective purchase price," which is constructed by dividing the total value of all purchases over the full year (summed across rounds) by the total quantity of all purchases over the full year. The dependent variable in Column 4 is "Effective sales price," which is constructed similarly. Columns 3-4 include only one observation per individual (per year). Round fixed effects are omitted in these specifications in order to estimate the effect of treatment on prices paid and received, which change because of shifts in the timing of transactions; therefore, round controls are not appropriate. Instead, we include year-fixed effects, as well as strata dummies. In all columns, "Treat" is an indicator of being in a treatment group. "Treat - R "x"" is an interaction between an indicator for being in a treatment group and an indicator for being in Round "x." "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Standard and Family-Wise Error Rate (FWER) p-values are presented in the notes for effective prices; the latter are calculated as specified in 2.2.1

	Net Sales		Effective Price	
	(1) Overall	(2) By rd	(3) Purchase	(4) Sales
Treat	0.186***		-57.449**	145.509***
	(0.063)		(27.156)	(41.767)
Treat - R1		-0.205**		
		(0.096)		
Treat - R2		0.384***		
		(0.104)		
Treat - R3		0.369***		
		(0.092)		
Observations	6740	6740	2014	1428
R^2	0.098	0.102	0.089	0.066
Mean DV	-0.421	-0.421	3085.372	2809.763
SD DV	2.038	2.038	534.511	504.822
P-Val Treat			0.035	0.001
P-Val Treat FWER			0.044	0.001

Notes: Significant at the ***[1%] **[5%] *[10%] level.

Table 6. **Market prices for maize as a function of local treatment intensity.** The dependent variable is price, as measured monthly following loan disbursal (Nov-Aug in Y1; Dec-Aug in Y2) in market surveys. Prices are normalised to 100 in Nov in low-intensity sublocations. "High" intensity is an indicator for a sublocation randomly assigned a high number of treatment groups. "Month" is a linear month-time trend (beginning in Nov at 0 in each year). Standard errors are clustered at the sublocation level. To check robustness to small cluster standard error adjustments, the notes present p-values from the standard specification compared to p-values drawn from the wild bootstrap procedure explained in 2.2.2.

	Dependent variable: Sales Price Trim				
	Main Specification (3km)			Robustness (Pooled)	
	(1) Y1	(2) Y2	(3) Pooled	(4) 1km	(5) 5km
High	4.410*	2.855	3.970**	2.787	3.766*
	(2.091)	(1.992)	(1.817)	(1.719)	(1.822)
Month	1.189***	1.224***	1.364***	1.327***	1.537***
	(0.363)	(0.377)	(0.350)	(0.339)	(0.291)
High x Month	-0.574	-0.476	-0.573	-0.520	-0.835**
	(0.422)	(0.459)	(0.386)	(0.390)	(0.366)
Observations	491	381	872	872	872
R^2	0.077	0.031	0.058	0.055	0.060
P-value High	0.051	0.171	0.044	0.124	0.056
P-value High Bootstrap	0.082	0.197	0.083	0.152	0.096
P-value Month	0.005	0.005	0.001	0.001	<0.001
P-value High Bootstrap	0.033	<0.001	0.026	0.016	<0.001
P-value High x Month	0.192	0.315	0.158	0.2	0.038
P-value High x Month Bootstrap	0.223	0.345	0.192	0.227	0.061

Notes: Significant at the ***[1%] **[5%] *[10%] level.

Table 7. **Inventory, net revenues, and HH consumption (log) effects, accounting for treatment intensity.** The dependent variable in Columns 1-3 is inventories, as measured by the number of 90kg bags of maize held by the household. The dependent variable in Columns 4-6 is net revenues, as measured by the value (in Ksh) of maize sales minus the value of maize purchases (the exchange rate during the study period ranged from 80 to 90 Kenyan shillings per USD). The dependent variable in Columns 7-9 is HH consumption (measured in logged Ksh), aggregated from a detailed 30-day recall consumption module. "Treat" is an indicator of being in a treatment group. "High" intensity is an indicator for residing in a sublocation randomly assigned a high number of treatment groups. Regressions include round-year fixed effects and controls for survey dates with errors clustered at the sublocation level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. "P-val T + TH = 0 provides the p-value from an F-test that the sum of the Treat and Treat*High equal zero. To check robustness to small cluster standard error adjustments, the notes present p-values from the standard specification compared to p-values drawn from the wild bootstrap procedure explained in 2.2.2.

	Inventory			Net Revenues			Consumption		
	(1) Y1	(2) Y2	(3) Pooled	(4) Y1	(5) Y2	(6) Pooled	(7) Y1	(8) Y2	(9) Pooled
Treat	0.759***	0.546***	0.740***	1059.602**	1193.768	1101.389**	0.012	-0.051	-0.011
	(0.189)	(0.185)	(0.155)	(437.732)	(685.048)	(430.091)	(0.040)	(0.040)	(0.023)
High	0.124	-0.028	0.017	533.903	-152.603	164.936	-0.003	-0.084	-0.047
	(0.355)	(0.219)	(0.241)	(551.179)	(558.948)	(479.685)	(0.051)	(0.053)	(0.043)
Treat x High	-0.333	-0.065	-0.291	-1114.628*	-555.215	-816.770	-0.013	0.174***	0.067*
	(0.229)	(0.255)	(0.192)	(535.594)	(804.864)	(520.036)	(0.052)	(0.055)	(0.037)
P-value Treat x High	0.165	0.802	0.149	0.054	0.501	0.136	0.802	0.007	0.091
Observations	3836	2944	6780	3795	2935	6730	3792	2944	6736
R^2	0.346	0.184	0.293	0.009	0.043	0.091	0.002	0.017	0.025
Mean DV	2.646	1.68	2.143	310.264	-3434.378	-1650.216	9.476	9.614	9.548
SD DV	3.52	2.871	3.234	6087.188	6093.296	6370.068	0.633	0.631	0.636
P-value T + TH = 0	0.006	0.015	0.006	0.864	0.146	0.408	0.97	0.006	0.081
P-value Treat	0.001	0.01	<0.001	0.028	0.102	0.021	0.767	0.228	0.627
P-value Treat Bootstrap	<0.001	<0.001	<0.001	0.061	0.129	0.059	0.758	0.212	0.614
P-value High	0.731	0.901	0.945	0.347	0.789	0.735	0.962	0.136	0.295
P-value High Bootstrap	0.764	0.911	0.951	0.39	0.804	0.766	0.962	0.139	0.313
P-value Treat x High Bootstrap	0.213	0.791	0.166	0.073	0.51	0.144	0.803	0.005	0.095

Notes: Significant at the ***[1%] **[5%] *[10%] level.

Table 8. **Distribution of gains in the presence of general equilibrium effects.** Calculations employ per-round point estimates on revenues β_1, β_2, and β_3 (coefficients on "Treat," "High," and "Treat x High" respectively) from Equation (5). These estimates are presented in Column 6 of Table 7 (in Ksh, multiplied by three to get the annual revenue gains; note the exchange rate during the study period ranged from 80 to 90 Kenyan shillings per USD). See appendix B for how numbers are calculated and the underlying assumptions. We have chosen not to round numbers as they are based on estimations described in appendix B

	Low Saturation	High Saturation
1. Direct gains/HH (Ksh)	3304.166	853.856
2. Indirect gains/HH (Ksh)	0.000	494.807
3. Ratio of indirect to direct gains	0.000	0.579
4. Direct beneficiary population (HH)	247.254	494.508
5. Total local population (HH)	3552.500	3552.500
6. Total direct gains (Ksh)	816968.241	422238.645
7. Total indirect gains (Ksh)	0.000	244686.240
8. Total gains (direct + indirect; Ksh)	816968.241	666924.886
9. Fraction of gains direct	1.000	0.633
10. Fraction of gains indirect	0.000	0.367

A Density of bootstrap

Through 5000 iterations of the WCB-t bootstrap method described in 2.2.2, we can plot the estimated parameter values $\hat{\boldsymbol{\beta}}$. As seen in figure 1 $\hat{\boldsymbol{\beta}}$ estimates can be approximated by a Student's-t distribution to infer the p-value from the t-statistic. For figure 2, the High and the T $\times$ High also seem to be Student's distributed for all combinations of parameters. However, this is not the case for the treatment alone, especially in the inventory and net revenue specifications, which invalidate the calculated p-value. This suggests that the treatment effect may be influenced by factors that create asymmetry in the impact of the treatment, leading to a violation of the assumptions for the standard p-values reported.

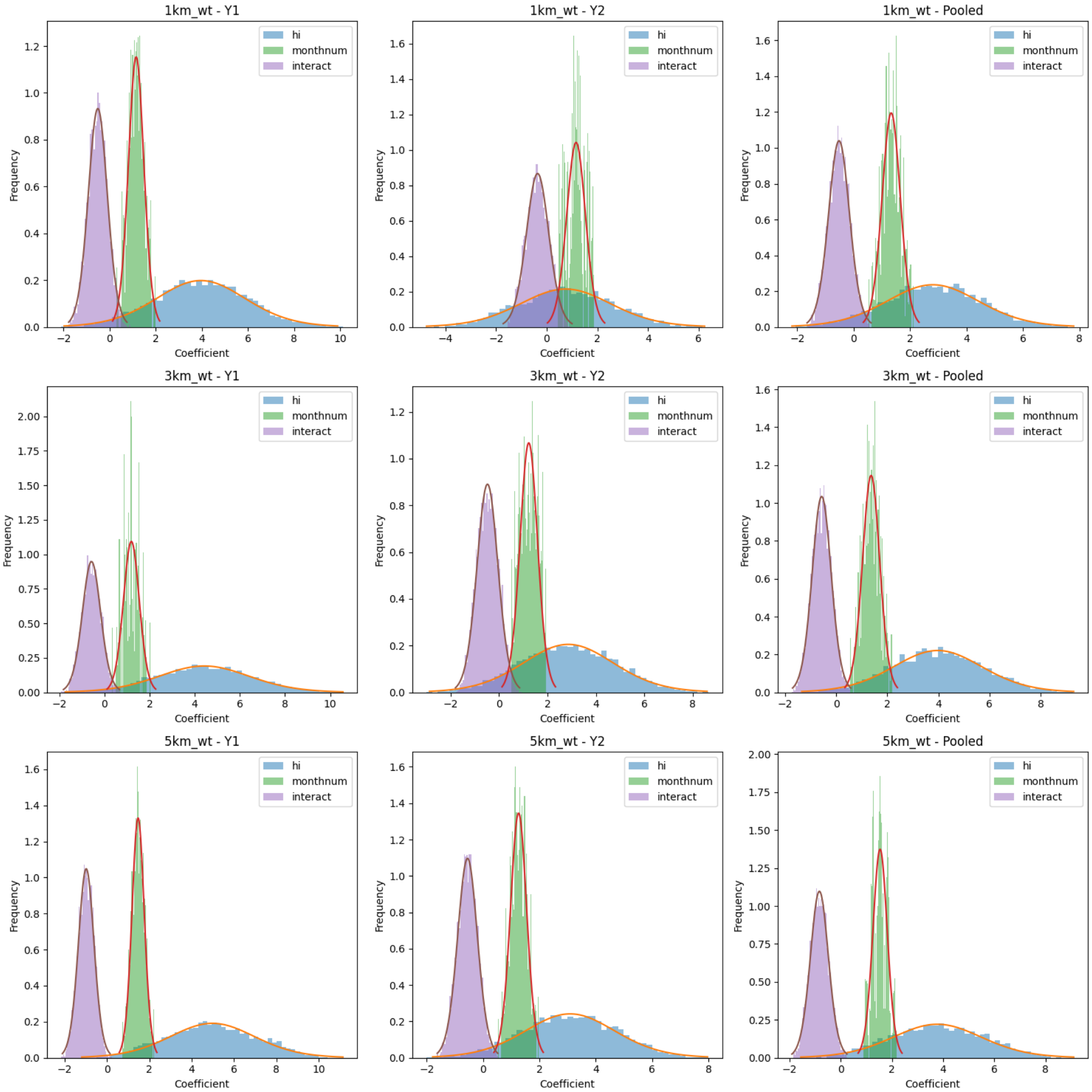

Figure 1. Density $\hat{\boldsymbol{\beta}}$ for the nine bootstrap regressions run for table 6 following the WCB-t procedure described in 2.2.2 with a fitted Student's-t distribution. Table 6 only presents the results of the estimates for a 3km radius and the pooled regressions for other radii. *hi* is the high treatment bool, *monthnum* is the monthly trend normalised to 0 in November, and *interact* is the interaction term between the two. Titles of each denote the respective radii and period. For radii, either 1km, 3km, or 5km are possible, and for periods, Y1 and Y2 are the first and second years, while Pooled is based on data across the two years

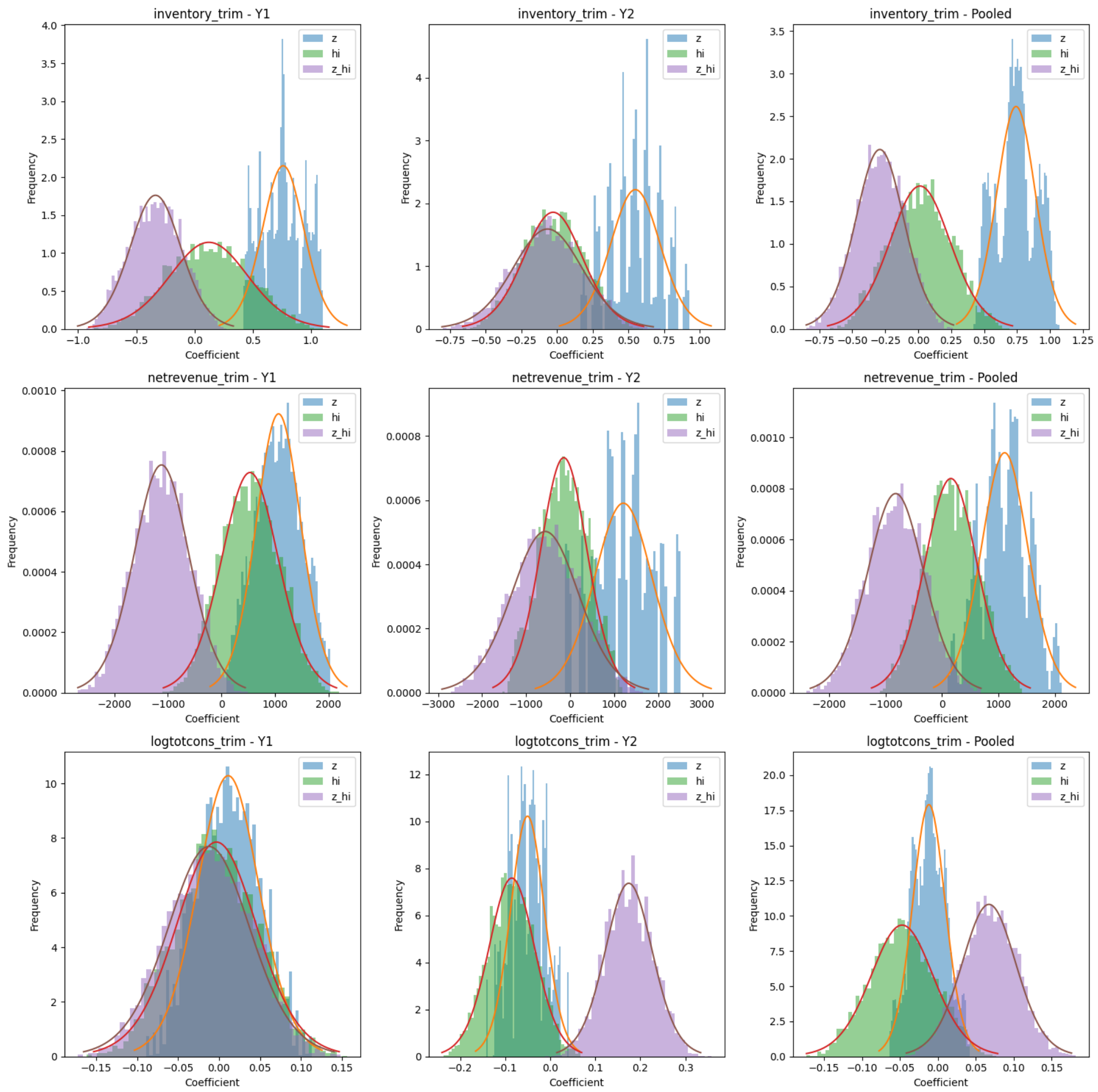

Figure 2. Density $\hat{\beta}$ for the nine bootstrap regressions run for table 7 following the WCB-t procedure described in 2.2.2 with a fitted Student's-t distribution. z denotes the Treatment bool, hi denotes the high intensity bool and z_hi is the interaction between the two. The title denotes the variable on the individual level we are using as the dependent variable and the period. The dependent variables are inventory, net revenue, and log consumption, all of which are trimmed for outliers. The periods Y1 and Y2 are the first and second years, while Pooled is based on data across the two years.

B Table 8 Assumptions

The following directly follows Appendix M.I of Burke et al., 2018c

Table 8 employs following summary statistics and assumptions:

1. Total population in the study area is 7,105 households (HH) (this figure is an approximation, as the sublocations used in this study are One Acre Fund (OAF) administrative districts and, therefore, do not directly correspond to the Kenyan census administrative districts. OAF estimates that it works with 30% of all farmers in the area. While this figure affects the total gains estimates, it does not affect any estimates of per-HH gains, ratios, or fractions in the table, nor does it affect any comparisons between low and high saturation areas) (A_1)

2. 50% of the study population resides in low saturation sublocations (this is roughly accurate; moreover, it allows a comparison of the size of the benefits across low and high saturation rates that is unconfounded by differences in underlying population sizes) (A_2)

3. 30% of HH in the region are One Acre Fund (OAF) members, a figure provided by OAF administrative records (A_3)

4. 40% of all OAF members were enrolled in the study in low saturation sublocations (A_{4a}) and 80% were enrolled in high saturation sublocation (A_{4b})

5. In each sublocation, 58% of individuals in the sample were randomly assigned to receive treatment (average across the pooled data from Year 1 and Year 2) (A_5)

Gains are estimated using the following calculations, using the above figures and the per-round point estimate on revenues β_1, β_2, and β_3 (coefficients on "T," "H," and "T x H" respectively) from equation (5). These estimates are presented in Column 6 of table 7 (in Ksh, multiplied by three to get the annual revenue gains; note the exchange rate during the study period ranged from 80 to 90 Kenyan shillings per USD):

- Low saturation direct gains: $3 \cdot \beta_1$
- High saturation direct gains: $3 \cdot (\beta_1 + \beta_3)$
- High saturation indirect gains: $3 \cdot \beta_2$
- Ratio of indirect to direct gains: $Row\ 2/Row\ 1$
- Low saturation direct beneficiary population (HH): $A_1 \cdot A_2 \cdot A_3 \cdot A_{4a} \cdot A_5 = 7,105 \cdot 0.5 \cdot 0.3 \cdot 0.4 \cdot 0.58$
- High saturation direct beneficiary population (HH): $A_1 \cdot (1 - A_2) \cdot A_3 \cdot A_{4a} \cdot A_5 = 7,105 \cdot 0.5 \cdot 0.3 \cdot 0.4 \cdot 0.58$
- Low saturation total local population: (HH): $A_1 \cdot A_2 = 7,105 \cdot 0.5$
- High saturation total local population: (HH): $A_1 \cdot (1 - A_2) = 7,105 \cdot 0.5$
- Total direct gains: $Row\ 1 \cdot Row\ 4$
- Total indirect gains: $Row\ 2 \cdot Row\ 5$
- Total gains (direct + indirect): $Row\ 6 + Row\ 7$
- Fraction of gains indirect: $Row\ 7/Row\ 8$
- Fraction of gains private: $1 - Row\ 9$