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Do capital grants improve microenterprise productivity?*

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Abstract

Can large capital injections increase the productivity of microenterprises? We use the lens of a production function to re-examine two previous randomised controlled trials that allocated capital grants to microenterprises. We find that productivity is higher for treated firms, and accounts for about 20-30 percent of the revenue effects of capital grants. We find that treatment tilts the asset composition towards durables with a technology component: a result consistent with an important role for capital-embodied technology. These productivity effects are still present six years after the grants, suggesting that capital injections can permanently shift microenterprise productivity.

JEL classification: L25, O12, O14, O17, O33

Keywords: Economic development, microenterprises, formality and informality, embodied technology, total factor productivity.

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1 Introduction

A large fraction of firms in developing countries are microenterprises with very low productivity. While these firms are an important source of income to their owners, they can drag down aggregate productivity and growth (Hsieh and Klenow, 2009). Making microenterprises more productive and competitive is therefore a key element of many policies that promote private sector development. However, this has turned out to be a major challenge (Bruhn, Karlan, and Schoar, 2018; Atkin, Khandelwal, and Osman, 2017; McKenzie and Woodruff, 2014). Other interventions that take a different angle – easing capital constraints – can have large and lasting effects on revenues and profits of microenterprises. However, little is known about the channels by which such effects occur. Do capital constraints only restrict capital, or do they also hold back productivity?

In this paper, we use the lens of a production function to look at the alleviation of capital constraints to microenterprises. This enables us to study directly how capital grants affect microenterprise productivity — a relationship that is not directly observable in survey data. In doing so, we conduct a secondary analysis of data from two related randomised control trials of capital grants to microenterprises: de Mel, McKenzie, and Woodruff (2008) in Sri Lanka (DMW henceforth) and Fafchamps, McKenzie, Quinn, and Woodruff (2014) in Ghana (FMQW henceforth). The experimental setup, combined with our estimate of total factor productivity (TFP), allows us to structurally disentangle the channels through which alleviating capital constraints increases revenues and profits. We estimate microenterprise production functions as well as TFP using the standard methods in the literature: a linear panel estimator, a control function estimator, and linear regression of labour productivity.

We find that the effects of capital grants cannot be fully rationalised either by adjustments of capital, intermediate inputs, or other production factors alone. Capital grants also have a sizable and significant effect on TFP, in particular by shifting TFP outward at the top of the distribution. They increase TFP of the median firm by about five to six percent; and by about seven to nine percent at the 80th percentile. We use the structure of the production function to perform a decomposition of treatment effects into factor adjustments and productivity. Between 19 and 29 percent of increase in revenue caused by capital grants can be attributed directly to an increase in productivity in Sri Lanka, and between 21 and 35 percent in Ghana — over and above adjustments of production factors.

Building on this main result, we exploit the richness of the asset data collected by DMW in Sri Lanka to explore how capital grants can affect TFP. One plausible channel through which this might occur is by introducing more advanced equipment and thus more efficient means of production. This channel is known in the growth literature as capital-embodied technical progress (Solow, 1960). We find that treated microenterprises are more likely than their control counterparts to invest into assets (such as vehicles or showcases) that are not essential to the core activities of a business, but which can be used in a way to run such activities more efficiently and to reach different market segments. Such assets acquired by treated firms also have a relatively higher technology component, based on a categorisation of individual asset items. Treated businesses are further able to expand their customer base, and to increase revenue from newly introduced products.

These results are sustained over a long time horizon. In Sri Lanka, where follow-up data are available six years after the experiment, we find that the increase in TFP and capital, and the tilt in the composition of fixed business assets, is similar five to six years after the experiment as in the first year. However, firms disinvest rapidly the stock of intermediate materials and goods that they purchased upon receipt of the grant. This suggests that capital grants have moved firms to a new trajectory with higher productivity and higher fixed capital, driven by a shift towards capital vintages with more embedded productivity.

Our paper contributes in two ways to understanding of the productive structure of microenterprises. First, to our knowledge, this is the first paper to consider and test the hypothesis that an increase in capital can enhance microenterprise productivity; our resulting estimates are therefore the first quantification of this channel for microenterprise growth. Access to better inputs in production has been recognised as a channel for productivity gains from trade (Amiti and Konings, 2007; Halpern, Koren, and Szeidl, 2015). The idea of capital-embodied technology dates to the early models of capital vintage by Johansen (1959) and Solow (1960). Griliches (1997) demonstrates the specific process of rent spillover, in which firms purchasing capital goods with embodied technology accrue some of the economic rent of this technology, if the supplier cannot perfectly price discriminate and the value of the technology is therefore not fully reflected in the price of the capital good. This channel has been shown to explain significant differences in cross-country productivity levels in agriculture (Caunedo and Keller, 2019), but has received almost no attention in the literature on microenterprises — or, indeed, in the applied microeconomic literature on firms.[1] Our results suggest that, even among some of the smallest firms in developing countries, differences in sales and productivity are at least partly driven by differences in basic technology adoption. More generally, our findings resonate with a wider literature on adoption of new technology and business practices (Atkin, Khandelwal, and Osman, 2017; Karlan, Knight, and Udry, 2015; Bloom, Eifert, Mahajan, McKenzie, and Roberts, 2013; Conley and Udry, 2010).

Our second contribution is to show that, with high-quality panel data, standard methods for production function estimation (Blundell and Bond, 1998; Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009; Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten, and Van Reenen, 2018) can be usefully applied to fit production

[1] Several qualitative studies report that owners of small firms identify technology as an important constraint of productivity and expansion (Aftab and Rahim, 1989; Kabecha, 1998).

functions for informal microenterprises. While linear panel methods (Arellano and Bond, 1991; Blundell and Bond, 1998) are our preferred estimator in this context where we expect measurement error to be potentially substantial, our estimates of production function coefficients as well as the estimates of the TFP effects of capital grants are very similar across methods.[2] Our estimates are significant, and reasonable in light of other estimates in the literature for larger establishments. In our view, this result — that such estimators can be applied effectively to microenterprises — opens new possibilities for a wide range of empirical applications in this and other contexts.

Our paper proceeds as follows. Section 2 describes the experiments and data. We outline our identification strategy for TFP estimates in section 3, present results in section 4, and interpret those results in section 5. Section 6 concludes.

2 Data and Experiments

We conduct our analysis using the experimental sample and survey data from two randomised control trials that allocated cash and in-kind grants to microenterprises in Sri Lanka (DMW) and in Ghana (FMQW).[3]

The Sri Lanka Microenterprise Survey was collected for the seminal work of de Mel, McKenzie, and Woodruff (2008). It spans a representative sample of 385 microenterprises, with a capital stock of less than 100,000 LKR (about \$1000), in retail, sales and manufacturing sectors. We mainly use the first nine waves; these are equally spaced, each spanning three months. The first wave started in April 2005. After the first wave (and, for a second set of firms, the third wave), half of the eligible firms were randomly assigned a cash or in-kind grant of either LKR 10,000 or LKR 20,000. The in-kind grants were purchased by the enumerators according to the free choice of the firm owners and could be spent on either or both of inventory and fixed assets. The smaller LKR 10,000 grants correspond to around three months of median profits and around 55% of the median capital stock in the base period. Relevant for the issue of technological upgrading, even the cash grants were used to purchase new materials or equipment, suggesting that owners expected positive returns to these items. On average, 43% and 18% of the 10,000 LKR cash grant and 34% and 16% of the 20,000 LKR cash grant were spent on the purchase of inventories and equipment respectively.

The Ghana Microenterprise Survey was collected for the work of Fafchamps, McKenzie, Quinn, and Woodruff (2014). FMQW surveyed 793 microenterprises, without paid employees or a motorised vehicle, in Accra and the neighbouring port town of Tema. Like

[2] Atkin, Khandelwal, and Osman (2017) and Keniston (2011) estimate microenterprise production functions using control function methods (Levinsohn and Petrin, 2003; Ackerberg, Caves, and Frazer, 2015).

[3] We summarise the data and experiments briefly, and refer the reader to de Mel, McKenzie, and Woodruff (2008) and Fafchamps, McKenzie, Quinn, and Woodruff (2014) for further details.

in Sri Lanka, survey waves were conducted every three months. The first wave started in November 2008, and the survey lasted for six waves.[4] Capital grants were randomly allocated after the second and the third wave; and for a small group, also after the fourth wave. The grant size was GHC 150, or about $120. Again, grants were either in cash or in kind, but unlike in Sri Lanka, there was no variation in the grant size. The grants are comparable in size to the smaller grants in Sri Lanka; in Ghana, they amount to two months of median baseline profits. Grants constituted a relatively larger shock to the capital stock of microenterprises in Ghana, and almost doubled median baseline capital of GHC 170.

Importantly, both surveys include the necessary variables on inputs (capital, labour, and intermediate goods purchases) that allow the estimation of production functions in the revenue form. We discuss details on the construction of variables for our analysis in Appendix A. In addition, the survey instruments as well as the main experimental design are very similar across the two contexts.

3 Microenterprise production functions

3.1 Methods for estimating production functions

The first step of our analysis consists of estimating a production function for microenterprises. We define TFP — as is very standard in empirical literature — as the residual from a Cobb-Douglas production function. In this section, we review the standard methods for estimating such production function coefficients, and discuss their advantages and shortcomings in the context of microenterprise production functions.

We postulate a standard Cobb-Douglas production function of the form

$$Y_{it} = A_{it} \cdot K_{it}^{\beta_k} \cdot L_{it}^{\beta_l} \cdot M_{it}^{\beta_m}, \tag{1}$$

where output Y_{it} of firm i in period t is determined by capital (K_{it}), labour (L_{it}) and materials (M_{it}); A_{it} is a Hicks-neutral technology term. Empirically, we know that firms in both experiments used a substantial share of their grants for the purchase of material inputs; in order to capture this fact in our analysis, we specify Y_{it} in terms of gross output (revenue).

Taking logs (which we denote in lower case), this becomes:

$$y_{it} = \beta_k \cdot k_{it} + \beta_l \cdot l_{it} + \beta_m \cdot m_{it} + \gamma_t + \omega_{it} + v_{it} \tag{2}$$

where $\ln(A_{it}) \equiv \gamma_t + \omega_{it} + v_{it}$. Note that, in this specification, we allow for three different types of unobserved shifters to TFP: (i) γ_t, a period specific shock, common to

[4] The authors also collected a later long-term follow-up wave, which we do not use.

all firms; (ii) ω_{it}, a time variant, firm specific shock which may be correlated over time; and (iii) v_{it}, a firm specific measurement error. This is a very standard specification in the empirical analysis of firm production functions (see, for example, Eberhardt and Helmers (2016)).

The main challenge for identification of the parameters β_k, β_l and β_m is the fact that firms choose inputs as a function of their firm-specific productivity shocks ω_{it}, which are unobservable to the researcher. This endogeneity is conventionally referred to as 'transmission bias' (see, for example, Gandhi, Navarro, and Rivers (2016)). Two standard approaches to overcome transmission bias are the estimation of the production function equation 2 in a dynamic linear panel framework, or to exploit the structural implications of a model of firm production for specifying a control function for productivity.

Dynamic linear panel methods exploit lags of output and input variables as instruments for endogenous inputs in a GMM framework. The main assumption of this class of estimator is that suitably lagged past input choices are independent of ω_{it}, but informative of current input choices due to adjustment costs, factor constraints, and other dynamic channels (Arellano and Bond, 1991; Blundell and Bond, 1998). Since we hypothesise that capital grants (through lagged capital choices) have a direct effect on productivity, we augment model (2) with a direct control for treatment status. It is worth noting that such estimators do not demand any assumption about firm optimisation; if, for example, the experimental treatments augment capital by easing a credit constraint, this does not pose any threat to our identification strategy.[5]

An alternative strategy is a class of estimators that introduce a control function term into equation (2): most commonly, a lagged polynomial of flexible inputs and capital. The resulting GMM moment conditions are then implied by structural assumptions about input choices.[6] The key economic assumption is invertibility, which requires that flexible inputs (such as materials) respond freely and monotonically to the current productivity shock, such that they can be used as a proxy for productivity. Although one might, on conceptual groups, expect measurement error and financial constraints to pose a challenge to invertibility for microenterprises, we show that the choice of estimator makes very little practical difference for production function estimates and for the estimates of productivity effects of capital grants in this context.

A third approach commonly used (see e.g. Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten, and Van Reenen (2018) for a recent example) does not try to identify the production function coefficients β_k, β_l and β_m in a first stage, but rather defines produc-

[5] Indeed, the identification of a linear production function estimator relies on adjustment costs or other optimisation frictions: Bond and Söderbom (2005), Gandhi, Navarro, and Rivers (2016), Shenoy (2018).

[6] Ackerberg, Caves, and Frazer (2015), section 2, provide a clear formal exposition of these approaches. Note that 'structural' in this context does not mean estimation of structural parameters that govern the choice problem, but rather deriving moment conditions directly from economic theory.

tivity as labour productivity, by rewriting (2) in terms of $\log(Y/L)$. This model is then augmented by the variable of interest — in our case, an indicator whether a firm has received experimental treatment in form of a capital grant — and estimated by OLS using the production factors as controls in the regression model with labour productivity as an outcome.

We implement all three approaches in our empirical section. To foreshadow our results, they all give very similar estimates of the productivity effects of capital grants. Our findings are therefore not driven by any particular set of assumptions regarding input choices, and robust to a wide range of commonly used productivity estimators.

3.2 Production function estimates

We present the main estimates for gross output production functions of microenterprises in Table 1. We estimate separately for Sri Lanka and Ghana. In columns 1 and 3, we report the estimates from the Blundell and Bond (1998) estimator, in which lagged variables serve as instruments for endogenous inputs in both levels and difference equations. The dynamic nature of productivity leads to the inclusion of the lagged dependent variable in the estimating equation. Various specification tests are informative about how to specify the lag structure, as well as to which degree lagged inputs are relevant instruments. Appendix B discusses this in more detail. In columns 2 and 4, we report results from the control function estimator, for comparison. These are obtained using the Wooldridge (2009) implementation of Ackerberg, Caves, and Frazer (2015).

< Table 1 here. >

For Sri Lanka (column 1), we estimate a coefficient on capital β_k of 0.18, a labour coefficient β_l of 0.13, and a materials coefficient β_m of 0.41. For Ghana (column 3), we estimate a capital coefficient of 0.19, a labour coefficient of 0.21, and a materials coefficient of 0.42. We note that, in both columns 1 and 3, the estimated models comfortably pass the relevant specification tests: the Hansen (1982) test of over-identifying restrictions, the Arellano and Bond (1991) autocorrelation test, and the Windmeijer (2018) test of instrument informativeness. Using alternatively the control function approach, for Sri Lanka we obtain very similar coefficients on all three input elasticities. For Ghana, we obtain a somewhat lower coefficient and capital and a higher one on materials, which could be a result of the less precise input measurement in these data compared to Sri Lanka.

Even before we turn to the TFP analysis, there are two important points worth noting about these estimates. First, the parameters are remarkably similar between Ghana and

Sri Lanka.[7] In this sense, our results speak to the issue of external validity and generalisability across experimental sites. They suggest that the similarity in reduced-form results between DMW and FMQW owes much to a deeper structural similarity in microenterprise production functions across contexts. Second, our estimates are broadly similar to production function estimates for larger establishments in developing countries. Specifically, we consider estimates for medium to large plants in Chile (Pavcnik, 2002; Gandhi, Navarro, and Rivers, 2016), Colombia (Gandhi, Navarro, and Rivers, 2016) and Ghana (Söderbom and Teal, 2004). We obtain approximately similar coefficient magnitudes as for those larger firms, and the same relative ordering of coefficient size that is commonly found in that literature ($\beta_m > \beta_l \geq \beta_k$).

We assess the robustness of these estimates in several ways. First, we note that production function estimates obtained from a control function approach — based on a starkly different set of assumptions — do not differ significantly from those obtained using linear panel methods. Further, in Appendix Tables A.1 and A.4, we report an extensive set of alternative specifications (OLS estimates, fixed effect estimates, dynamic panel estimates with alternative instruments, and Ackerberg, Caves, and Frazer (2015) estimates). In general, our results remain remarkably stable across these alternative specifications. This provides reassurance that our preferred estimates are reasonable, in the sense that they do not change drastically with different specifications or estimators.

Second, in Appendix Tables A.2 and A.5, we show that it is reasonable to pool data from treatment and control firms; this rules out an alternative explanation of our results, in which the treatment serves somehow to shift the production function parameters, rather than acting through a TFP channel. Similarly, in Appendix Tables A.3 and A.6, we show that it is reasonable to pool production functions from different industries, in particular between traders and non-traders.

4 The productivity effects of capital grants

4.1 Do capital grants affect total factor productivity?

We now turn to the question of whether capital grants are productivity-enhancing. To estimate the treatment effect of capital grants on productivity, we follow standard procedure from the experimental literature, comparing outcome distributions between treatment and control groups. Our object of interest is the distribution of total factor productivity (TFP), which we construct as:

$$\widehat{TFP}_{it} = \exp\left(y_{it} - \hat{\beta}_k \cdot k_{it} - \hat{\beta}_l \cdot l_{it} - \hat{\beta}_m \cdot m_{it}\right) \tag{3}$$

[7] When we run a cross-equation test of whether these production functions are the same in Sri Lanka as in Ghana, this comfortably passes for our preferred linear panel estimator ($p = 0.71$). When we run the same test for the control function estimators, we reject the null of parameter equality ($p = 0.02$), though the coefficients from the control function estimation are nonetheless quite similar to each other.

where $\hat{\beta}_k$, $\hat{\beta}_l$ and $\hat{\beta}_m$ are the estimated production function coefficients.

Table 2 presents our main result, for the three standard productivity measures: TFP from a Blundell and Bond (1998) estimation, TFP from a control function estimator (here, Wooldridge (2009)) and labour productivity (revenue over total hours, not requiring any production function estimation). We estimate TFP effects at the mean, and at various quantiles of the distribution. We pool across samples from Ghana and Sri Lanka to maximise statistical power. Our regressions include survey wave and industry controls, separately by country, and control for baseline values of the dependent variable. Our results are remarkably stable across the three outcomes. We find that treatment increases productivity significantly by 5-6 percent on average, as well as at the median. We find particularly an outward shift at the top of the distribution: productivity increases by 7-9 percent at the 80th percentile. We obtain quantitatively very similar results when we omit baseline controls from the estimation (Appendix Table A.7), estimate separately for Sri Lanka and Ghana (Appendix Tables A.8 and A.9), or compare productivity distributions non-parametrically (Figure A.1).

< Table 2 here. >

These findings suggest the effect of capital grants on profits does not work through the adjustment of the production factors capital and materials (and labour) alone. There is an additional effect of grants on output which is loaded onto productivity. This increase in productivity comes from the top of the distribution: capital grants enable the relatively most productive microenterprises to become more productive. An alternative interpretation is that the production function residual reflects higher markups or sales margins for treated firms, rather than differences in productivity/TFP. However, the available data are inconsistent with such an interpretation. In Appendix Figure A.2, we show that sales margins from the main product in Sri Lanka are, if anything, lower for treated than for non-treated firms.

The differential effects of capital interventions in informal firms by gender are of significant interest in the literature: for example, they were specifically taken into account in the experimental design in the Ghana study, and have recently been further investigated in Bernhardt, Field, Pande, and Rigol (2017). While this is not the focus of this paper, we nevertheless test for this in both datasets. Our results are inconclusive, and we note that our tests have low power. We find suggestive evidence of higher treatment effects for men in Sri Lanka, and for women in Ghana. However, we note that we cannot reject the null hypothesis of equal treatment effects across gender in either setting. In Ghana, we also find some evidence that TFP effects are higher for in-kind treatments.[8] These find-

[8] These results are in Appendix Table A.12. For Sri Lanka, we cannot reject the null hypothesis that cash and in-kind treatments have the same effect (Appendix Table A.13). The point estimates are somewhat higher for cash treatments.

ings put another perspective on the 'flypaper effect' for female microenterprise profits reported by FMQW.

4.2 What kind of capital do capital grants buy?

After documenting the effects of capital grants on residual TFP, we now shed more direct light on the ways in which capital grants can enhance productivity. In particular, we explore the hypothesis that this occurs through technology embodied in capital. For evidence, we turn to the detailed listing of capital assets in the questionnaire from DMW in Sri Lanka.[9] The questionnaire lists individual assets in the following categories: business tools or utensils, machinery, furniture and equipment, vehicles, and other physical assets (excluding inventories). We make use of these categories, and additionally hand-code individual items according to whether they have a more advanced technology component. To give a few examples, we code electronic scales as higher-technology, but not scale weights. Battery chargers, motorised vehicles, glass showcases and hair dryers are higher-technology; tires and tubes, bicyles, wooden tables and scissors are not.

Microenterprises in the treatment group acquire different assets than the control group, and those assets are technologically more advanced. Table 3 displays the effects of capital grants on different categories of microenterprise capital. As before, we report coefficients on treatment dummy from ANCOVA regressions. This is not surprising, given that data on individual asset categories is highly heterogeneous and sparse. We find that, pooled across follow-up waves, microenterprises increase their fixed capital stock by about as much as their inventories stock; although only the former is statistically significant. Within fixed assets, most of the investment occurs in vehicles and in assets classified as 'other durable goods' — they increase by about 2,600 rupees (about 26 USD) or 70% relative to the control mean, compared to machines tools and furniture which increase by about 10% relative to the control mean. Almost all of these durables that treated firms acquire are classified as technologically more advanced. Thus, when we separate assets by their technology content, we find that high-technology assets increase significantly by about 2,800 rupees or about a quarter of the control mean.[10]

< Table 3 here. >

Detailed qualitative evidence on the type of assets purchased gives us another angle to understand how capital grants change the composition of capital. Among the most

[9] While FMQW use a similar questionnaire in Ghana, they do not ask for a list of individual asset items together with their names.

[10] In Appendix Table A.14 we provide a more detailed breakdown of effects by asset category, as well as for the extensive margin (asset ownership). The results further support our interpretation here.

commonly purchased assets in the treatment group are vehicles, refrigerators, and showcases.[11] Refrigerators and showcases make up around 60% of other durable assets, both by quantity and by value.

This evidence indicates that capital grants tilt the composition of fixed capital items in firms, and that investment following capital grants is not homothetic across assets. Treated microenterprises do not invest more into asset categories that are core to running the firm — such as machinery, which comprises almost half of the average capital stock in control firms. Instead, treated firms acquire assets that previously played a more marginal role: durable goods such as refrigerators and showcases, as well as vehicles.[12] Such items are often not essential for carrying out the small-scale manufacturing, trade and service activities that small Sri Lankan firms engange in. But they can allow business owners to carry out their activities much more effectively — and perhaps even in a qualitatively different ways that reaches new market segments. We find some suggestive evidence of this. Treated firms sell to a larger number of customers within a given day, and significantly increase their share of sales from newly introduced products; although from a very low baseline mean.

Finally, to study potential capital lumpiness, we look at the unit prices of asset purchases. Treated firms acquire somewhat more expensive assets after receiving capital grants (see Appendix Figure A.5). Treated microenterprises are also more likely to purchase 'big ticket items'. For instance, a third of treated firms purchased an item with unit value of more than 40 USD (roughly the average monthly profit at baseline), but only 18% of control firms.[13] On the other hand, even at baseline, about half of the firms at least one individual item worth 40 USD or more. If the lumpiness of capital is a reason why control firms do not buy productivity-enhancing assets, then this must be a constraint at the margin, not a constraint for the average capital stock of microenterprises.

5 Interpretation

5.1 Are productivity and capital effects sustained over time?

Improvements in microenterprise productivity are especially noteworthy because they can potentially shift firms into a new, higher steady-state of capital, revenue and profits.

[11] These items are much less commonly purchased by the control group. Even though the number of cases are small, the anecdotal evidence suggests that increases in these asset categories are substantial. For instance, after receiving capital grants, the number of refrigerators doubles, and the number of bicycles and showcases increases by 50 percent.

[12] At baseline, 90% of all firms own tools, machinery or furniture; at endline 96% do both in the treatment and in the control group. On the other hand, only 30% of microenterprises denote assets in the categories that we denote as non-essential, such as vehicles and durables. Appendix Figure A.3 graphs this evolution of asset ownership.

[13] This remains true if we vary this (arguably arbitrary) threshold; results are available upon request.

As any standard production framework would suggest, long-term changes in firm size require a change in productivity (or other fundamentals) for the firm (see, for example, the theoretical framework in FMQW). By contrast, in the standard model of firm production with fixed productivity, we would expect firms who received capital grants either to revert to a steady state they occupied previously, or to converge over time to the same steady state as the control group. In both of these cases, any treatment effect should fall back to zero over time. However, if grants increase productivity, then treated firms will be pushed towards a new, higher steady-state size, in which they will permanently have a higher capital stock and higher profits (as well as higher productivity).

We turn to the long-term follow up data for Sri Lanka to assess whether productivity improvements and shifts in the asset composition are sustained over time. de Mel, McKenzie, and Woodruff (2012) report a sustained increase in profits for the treatment group more than six years after the initial capital grants.[14] In Table 4 we include these long-term follow-up surveys into our data, and report dynamic treatment effects separately by the year since the capital grant was given. We find that TFP, fixed capital, as well as the tilt in the capital composition are sustained throughout the years. About six years after the intervention, estimates for each of these outcomes are similar or even larger to those in the first year after treatment; although the long-term data seems to be much noisier, such that no individual coefficient at this horizon is statistically significant. However, year-by-year treatment effects up to three years post-treatment are of similar magnitude and mostly individually significant.

< Table 4 here. >

Where we do find significant disinvestment over time is in the stock of goods and materials that the firms hold in inventory. Firms decapitalise inventories quickly after the first year, such that stocks in any subsequent year revert back to the level of the control group. This evidence suggests that the most profound change in microenterprises immediately after treatment — a strong increase in inventories, which account for two thirds of business purchases from the grants — cannot explain the sustained increase in productivity and profits. This rules out an alternative explanation that productivity effects in this context are driven by a higher level inventories, for example through reduced stock-outs, better customer choice, or lower re-stocking costs potentially associated with higher inventories stocks. Rather, this pattern of results over time again points to technology-embodied capital as the channel.

If entrepreneurs do not have immediate full knowledge of the productivity effects of investing into new, productivity-enhancing assets, they might be reluctant to try out a

[14] In Ghana, FMQW find significant effects about three years after treatment. Their three-year follow up data, however, does not contain the variables that we would need to calculate productivity.

risky investment (Atkin, Khandelwal, and Osman, 2017; Conley and Udry, 2010). While durables, vehicles and other assets with higher technology components as well as TFP increase immediately upon grant receipt, there is no catch-up from the control group. This suggests that the windfall from grants allowed individuals to purchase assets that they would otherwise not have acquired. These asset purchases are clustered in the period immediately after the grant payout; there is no crowding-in of follow-up investment (Appendix Figures A.3). Similarly, control firms do not acquire these productivity-enhancing assets: even three years after the grants, the initial differences in vehicles and durables ownership that opened up between the treated and control microenterprises prevails (Appendix Figure A.4).

5.2 How important are the productivity effects of capital grants?

Finally, we turn to the question of how much of the effect of capital grants is driven by productivity, and how much is driven by other channels. By imposing the production function in equation 2, we can decompose the average treatment effect (ATE) of capital grants on revenue as follows:

$$\mathbb{E}\left(\frac{\Delta y_{it}}{\Delta z}\right) \approx \mathbb{E}\left(\frac{\Delta a_{it}}{\Delta z}\right) + \beta_k \cdot \mathbb{E}\left(\frac{\Delta k_{it}}{\Delta z}\right) + \beta_l \cdot \mathbb{E}\left(\frac{\Delta l_{it}}{\Delta z}\right) + \beta_m \cdot \mathbb{E}\left(\frac{\Delta m_{it}}{\Delta z}\right), \qquad (4)$$

where $a_{it} = \ln A_{it}$ is the log of TFP and z is treatment status (which in our case is binary).[15] Equation 4 breaks down the revenue effects of capital grants into the contributions associated with adjustments to production factors, and changes in TFP. Replacing population quantities with sample analogues (our estimated coefficients of the production function, and estimated treatment effects on inputs and TFP) lets us immediately compute this decomposition.

We report the results from the decomposition in Table 5. Since production function coefficients differ by country, we report separate results for Sri Lanka and Ghana. We further report separate decompositions for each method we use to estimate TFP.[16] We find that changes in TFP account for 19–29% of the treatment effect of capital grants on revenues in Sri Lanka, and 21-35% in Ghana. The increase in capital stock accounts for about 20% on average, and higher material use contributes on average to around 50% of the increase in revenues. The contribution of changes to labour input on revenues is neglible; it is even slightly negative in Ghana. This is due to a very small but negative

[15] This derivation is mathematically quite similar to the decomposition applied by growth accounting, which splits GDP growth into its components, based on the aggregate production function. Note, for example, that for $\Delta z \to 0$, the relationship can be expressed in partial derivatives, and the relationship becomes exact, rather than an approximation.

[16] The treatment effects on production factors are not dependent on the TFP estimation method and therefore do not vary within a country. Contributions of these factors do vary since they again depend on the estimated production function coefficients

treatment effect on labour inputs.

< Table 5 here. >

Our results suggest that the productivity effects of capital grants are economically meaningful. We draw this conclusion especially in light of the direction in which a potential endogeneity of inputs to productivity influences our decomposition. Any model of firm behaviour would suggest that inputs are chosen as a function of TFP. Thus, the direct (partial) contribution of TFP will in general not be an accurate estimate of the *total* contribution of TFP to the effects of capital grants. We expect the partial contribution to be an underestimate of the total contribution, since we expect the relation between inputs and TFP to be positive. Thus, our decomposition likely provides a lower bound to the overall contribution of productivity to the effects of capital grants. The degree to which the direct effect understates the total effect depends on how freely firms can adjust inputs in response to productivity shocks.

6 Conclusion

In this short article, we look at microenterprises through the structural lens of a production function. We show that we can successfully fit production functions to microenterprises. This enables us to analyse the effects of capital grants on productivity. We find that capital grants to microenterprises in Sri Lanka and Ghana have significant and lasting effects on total factor productivity. A decomposition analysis suggests that returns to capital grants for microenterprises contain a significant return to increased productivity, which adds a more nuanced interpretation to the previous assumption in this literature that treatment effects are returns to capital alone. We find evidence for a plausible mechanism behind this: capital items that embody superior technology allow firms to improve total factor productivity. These findings speak to a broader policy debate on how to address the persistence of small informal firms in developing countries (Hsieh and Klenow, 2009; Meghir, Narita, and Robin, 2015).

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Tables and Figures

Table 1: **Production functions estimates for microenterprises in Sri Lanka and Ghana**

	Sri Lanka		**Ghana**	
Specification:	(1) Blundell-Bond	(2) Wooldridge	(3) Blundell-Bond	(4) Wooldridge
Log capital	0.18**	0.16***	0.19***	0.08***
	(0.07)	(0.02)	(0.07)	(0.02)
Log labour	0.13***	0.20***	0.21***	0.19***
	(0.05)	(0.03)	(0.05)	(0.03)
Log materials	0.41***	0.45***	0.42***	0.55***
	(0.06)	(0.03)	(0.09)	(0.02)
L.Log revenue	0.37***		0.22***	
	(0.06)		(0.04)	
Observations	2610	2499	3105	2313
Microenterprises	382	379	770	724
Hansen (p-value)	0.10		0.45	
$\hat{\beta}_k + \hat{\beta}_l + \hat{\beta}_m$	0.72		0.81	
Constant returns (p)	0.00		0.04	
AR(1) (p)	0.00		0.00	
AR(2) (p)	0.52		0.24	
Instruments	77		45	
Underidentification (p-values):				
Log capital	0.01		0.00	
Log labour	0.00		0.00	
Log materials	0.00		0.00	
L.Log revenue	0.01		0.00	
L.Log capital				
L.Log labour				
L.Log materials				

Note: Estimators employed are Blundell and Bond (1998) System GMM and the Wooldridge (2009) implementation of Ackerberg, Caves, and Frazer (2015). All models partial out for wave dummies and post-treatment status (not reported). We report p-values for the Hansen (1982) test of over-identifying restrictions, the Arellano and Bond (1991) autocorrelation test, and the Windmeijer (2018) test of instrument informativeness. Samples are equivalent to the preferred samples in the respective original studies. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table 2: **Capital grant treatment effects across all measures of productivity**

	(1) ANCOVA	(2) Quantile (0.2)	(3) Quantile (0.4)	(4) Quantile (0.5)	(5) Quantile (0.6)	(6) Quantile (0.8)
A. Dependent variable: log(TFP) estimated using Blundell-Bond estimator						
Dummy: Treated	0.06*	0.02	0.03	0.06*	0.09***	0.09**
	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)
Observations	4777	4777	4777	4777	4777	4777
Microenterprises	1114	1114	1114	1114	1114	1114
B. Dependent variable: log(TFP) estimated using Wooldridge estimator						
Dummy: Treated	0.05*	0.00	0.04	0.05	0.09***	0.08**
	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Observations	4777	4777	4777	4777	4777	4777
Microenterprises	1114	1114	1114	1114	1114	1114
C. Dependent variable: log(revenue/hours worked)						
Dummy: Treated	0.05*	0.01	0.03	0.05**	0.06**	0.07**
	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)
Log(Capital/labour)	0.09***	0.04*	0.04***	0.05***	0.07***	0.10***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Log(Materials/labour)	0.58***	0.73***	0.73***	0.70***	0.67***	0.57***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Log labour	-0.09***	-0.04	-0.06**	-0.06***	-0.07***	-0.12***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	4777	4777	4777	4777	4777	4777
Microenterprises	1114	1114	1114	1114	1114	1114

Note: This table reports the effect of treatment on TFP at different moments of the distribution, for microenterprises in Ghana and Sri Lanka. In Panel A, TFP is estimated using the Blundell and Bond (1998) System GMM estimator. In Panel B, TFP is estimated using the Wooldridge (2009) implementation of Ackerberg, Caves, and Frazer (2015). In panel C, the dependent variable is the standard measure of labor productivity. All regressions include wave-times-survey and industry-times-country fixed effects; and control for baseline outcomes. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table 3: **Effects of capital grants on microenterprise capital, market and product scope**

	(1) Inventories	(2) Fixed capital	(3) Machines, tools & furniture	(4) Vehicles & other durables	(5) Low-tech capital	(6) High-tech capital	(7) Customers	(8) New product introduction	(9) New product sales
Dummy: Treated	3904.62**	3594.79***	688.70	2630.88***	697.04**	2814.05***	2.27*	0.01	0.40**
	(1608.33)	(961.61)	(712.43)	(625.69)	(320.58)	(892.88)	(1.23)	(0.01)	(0.19)
Control mean	14,015	15,555	11,581	3,763	4,717	10,838	12	0	1
Observations	3,358	3,341	3,329	3,345	3,341	3,341	3,288	2,251	2,911
Microenterprises	385	385	385	385	385	385	385	385	385

Note: This table breaks down the effect on grants on different categories of capital (columns (1)–(6)) and on market and product scope (columns (7)–(9)). Fixed capital is broken down by functional category in columns (3) and (4) following the DMW questionnaire, and into technology components in columns (5) and (6) based on our coding. Outcome in colummn (7) are number of customers on last business day; in column (8) whether a new product was introduced in the last 3 months; and the percentage of sales going to the new product (coded zero for firms without product introduction). Specifications are ANCOVA when the dependent variable at baseline is available (columns (1)–(7)). All regressions control for wave dummies. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table 4: **Long-term effects of capital grants on productivity, capital, and intermediate inputs**

	(1) ln(TFP)	(2) Fixed capital	(3) Machines, tools & furniture	(4) Vehicles & other durables	(5) Low-tech capital	(6) High-tech capital	(7) Inventories	(8) Total expenditure
Dummy: Treated × Year 1	0.09*	4006.32***	1211.88*	2681.68***	576.17*	3357.29***	5061.97***	4340.33**
	(0.05)	(997.69)	(654.18)	(658.34)	(326.40)	(898.31)	(1552.18)	(1953.94)
Dummy: Treated × Year 2	0.11**	3429.04**	914.64	2510.42***	702.30	2648.49**	2671.51	3272.91
	(0.06)	(1365.87)	(1007.41)	(755.05)	(447.40)	(1205.17)	(1855.43)	(2604.60)
Dummy: Treated × Year 3	0.05	3480.80*	900.29	2345.26**	976.40	2435.44	643.78	3431.19
	(0.07)	(1865.63)	(1402.32)	(924.58)	(700.92)	(1542.89)	(2129.55)	(3420.30)
Dummy: Treated × Years 5-6	0.08	4603.97	918.72	4355.67			827.50	1424.98
	(0.07)	(4131.12)	(2742.95)	(2980.97)			(2260.96)	(1947.52)
Control mean: baseline	-0	12,624	9,257	3,262	3,941	8,683	14,131	8,832
Control mean: 3 years	0	22,647	15,070	6,963	7,424	15,224	14,606	27,785
Observations	4,164	4,763	4,749	4,767	4,197	4,197	4,749	4,650
Microenterprises	385	385	385	385	385	385	385	385
p-value: Year 1 = Year 2	0.53	0.44	0.62	0.64	0.56	0.30	0.06	0.45
p-value: Year 1 = Year 3	0.52	0.73	0.78	0.64	0.47	0.46	0.01	0.72
p-value: Year 1 = Year 4	0.92	0.88	0.91	0.58			0.06	0.14

Note: This table shows the evolution of effects of capital grants on TFP, assets and materials for up to six years after treatment. TFP is from the preferred Blundell-Bond estimator. All other variables are as defined in Table 3. In additional, total expenditure in column (8) is total business expenditure in the last month, minus the wage bill. Breadown of individual asset items not available in year 5 and 6 surveys. All regressions are ANCOVA and control for wave dummies. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table 5: **Decomposing the effect of capital grants on revenue**

Sample:	**Sri Lanka**			**Ghana**		
Production function estimates:	Blundell-Bond	Wooldridge	OLS (Y/L)	Blundell-Bond	Wooldridge	OLS (Y/L)
Treatment effect: Revenue	0.202	0.202	0.202	0.140	0.140	0.140
Treatment effect: TFP	0.059	0.054	0.038	0.049	0.048	0.030
Treatment effect: Capital	0.307	0.307	0.307	0.173	0.173	0.173
Treatment effect: Materials	0.190	0.190	0.190	0.140	0.140	0.140
Treatment effect: Labour	0.050	0.050	0.050	-0.007	-0.007	-0.007
Contribution: TFP	0.290	0.268	0.190	0.352	0.346	0.212
Contribution: Capital	0.280	0.247	0.168	0.234	0.103	0.131
Contribution: Materials	0.381	0.420	0.593	0.416	0.553	0.622
Contribution: Labour	0.033	0.049	0.056	-0.011	-0.010	-0.010

Note: This table decomposes the effect of capital grants on revenue into the contribution of TFP and the contribution of production factors, following equation 4. Average treatment effects (ATE) are estimated with OLS. Relative contributions of each factor are calculated according to equation (4) by multiplying ATE with factor elasticities, divided by ATE on revenues. Factor elasticities and TFP treatment effects are specific to the production function estimate used in each column; and are reported in earlier tables. Treatment effects on revenue, capital, materials and labour are common for each sample. We apply the same sample restriction as for the production function estimation, retaining observations with non-missing data on revenues and all inputs. Contributions may not add up to 1 due to rounding.

Online Appendix

A Data construction

We use the public data sets and replication files available from the author's web sites. Whereever possible, we use variables as cleaned and processed by DMW and FMQW. We refer the reader to de Mel, McKenzie, and Woodruff (2008) and Fafchamps, McKenzie, Quinn, and Woodruff (2014) for further details. Here we summarise the main aspects of data construction, in particular of the variables used in production function estimation.

Revenue (output) is the total sales revenue during the reference month – the last month before the survey – across all respective activities of a business: manufacturing, trade, and services.

Capital is the total current value of business assets, excluding land. This follows the variable construction by DMW and FMQW. The value of capital is constructed using the perpetual inventory method: initial value of capital stock + new additions to capital stock + repairs and improvements to existing capital stock − sales and damages of capital stock. Assets are elicited item by item, in a number of categories. Respondents estimate the value of each item; the total is then calculated by summing over all items. In Sri Lanka – but not in Ghana – the name of the item is additionally recorded.

Labour is the total number of hours worked in the last week by the business owner, family members, other unpaid workers, and any paid workers in the business.

Materials is the total value of business expenses, in the reference month, for the purchase of materials and items for resale, and the purchase of electricity, water, gas, and fuels.

Nominal currency values are deflated by the respective monthly consumer price indices. We winsorise all these variables, over the pooled data in each survey, at the respective top and bottom 1%. We then use log values to estimate production functions.

B Implementation of production function estimation

We construct our estimate of TFP with factor elasticity estimates that we obtain from a gross output production function[17] estimated using the Blundell and Bond (1998) "system GMM" estimator, as well as with the Wooldridge (2009) GMM implementation of

[17] The alternative would be to denote Y_{it} as value added. In a value-added production function, the contribution of intermediate inputs is netted out and the production of value added is expressed in terms of capital and labour only. This transformation can be theoretically justified in the special case where the production function is Leontieff in materials (Gandhi, Navarro, and Rivers, 2016); however, we do not view that as a reasonable restriction for this context.

the control function approach. Here we review these methods in more detail than in the main text, and discuss a number of choices that we make in implementation, as well as evidence that guides our choices.

B.1 Linear panel System GMM

Blundell and Bond (1998) develop a set moment conditions under which the parameters of an autoregressive linear panel data model are identified. Applying this more general method to production functions places a restriction on equation 1 – namely, that the evolution of ω_{it} over time follows a linear AR(1) process, and not some arbitrary Markovian process. In our view, this is a fairly mild restriction, in addition and compared to the structural assumptions that literature makes by default, such as that the production function is Cobb-Douglas. In addition to the three error term component specific in equation 2 of the main text, the dynamic linear panel approach — but not the control function methods — is able to accommodate firm-level fixed effects η_i. A second additional assumption in Blundell and Bond (1998) restricts the 'initial condition' – namely initial *growth* of inputs and outputs of the firm needs to be uncorrelated with the firm fixed effect.

The GMM estimator relies on two sets of moment conditions, of the respective form:

$$E(x_{i,t-s}\,\Delta e_{it}) = 0 \qquad s \geq S \tag{A.1}$$

$$E(\Delta x_{i,t-m}\,e_{it}) = 0 \qquad m \geq M \tag{A.2}$$

where Δe_{it} is the error term from a first-differenced dynamic specification, which includes a lagged dependent variable. Similarly, e_{it} the error term from the levels equation. What these moment conditions say is that suitable lags of variables x_{it} (inputs and output) of the production function serve can serve as instruments in the difference equation; and lags in differences can serve as instruments in the levels equation.

Unlike in the control function approach, the lag structure (i.e. how many periods s or m we have to lag variables such that they become valid instruments) in Blundell and Bond (1998) estimation tends to be informed by empirical specification tests, not by a priori assumptions about the structure of production process in the firm. Our choice of lag structure is informed by three such specification tests. First, since the model includes many more instruments than endogenous regressors, the Hansen (1982) test of overidentifying restrictions helps judge the validity of the moment conditions. Under the null hypothesis that the moment conditions hold, the test statistic follows an asymptotic chi-squared distribution. Hence the test passes if we do not reject the null.

Second, the Arellano and Bond (1991) test for serial correlation in the residuals helps us judge whether the estimated model is dynamically complete, i.e. whether the assumption of an AR(1) structure of productivity is satisfied. The null hypothesis is that that there is no correlation in the residuals in the dynamic model. This means that the inclusion of a lagged dependent variable makes the model dynamically complete. In other words, the lagged dependent variable is a sufficient control for any correlation in the residual. Under the null, the first-differenced residuals are negatively autocorrelated, but the residuals of higher order are uncorrelated. The Arellano and Bond (1991) test therefore passes if we do not reject the null hypothesis of an AR(1) process, but reject the null hypothesis of an AR(2) process.

Third, the Windmeijer (2018) underidentification test is informative about the strength and relevance of instruments. Whereas the choice of the first suitable lags S and M are primarily guided by the need to satisfy the moment conditions, further lags will generally satisfy these conditions even more comfortably. However, increasing the distance of lags means that lags tend to lose their predictive power over current variables. Windmeijer (2018) develops a test which extends the Cragg-Donald and Kleibergen-Papp weak instruments tests to models with clustered and heteroskedastic errors, with a particular application to linear dynamic panel models. The test procedure allows for testing instruments for each endogenous variable in turn. The Windmeijer (2018) test passes if we reject the null hypothesis that instruments have no predictive power.

Our choice of lag structure in Table 1 is informed by these three sets of test, by coefficient stability in Appendix Tables A.1 to A.6, and by a preference for parsimony. Our preferred specifications include the following set of lags as instruments:

Variable	Output	Capital	Labour	Materials
Sri Lanka lags	{2, 3}	{3, 4}	{1, 2}	{2, 3}
Ghana lags	{1, 2}	{2, 3}	{1, 2}	{2, 3}

In total, this gives us 79 instruments (in differences and levels) in Sri Lanka, and 51 instruments in Ghana. In both cases, each of the specification test passes at conventional levels of significance.

B.2 Control function estimators

Control function estimators are an alternative method, first introduced by Olley and Pakes (1996) and subsequently and substantially developed by Levinsohn and Petrin (2003), Ackerberg, Caves, and Frazer (2015), and Wooldridge (2009). The strategy essentially amounts to introducing a control function term into equation (2): most commonly, a lagged polynomial of flexible inputs and capital. The resulting GMM moment conditions are then implied by structural assumptions about input choices. The key economic assumption is invertibility, which requires that flexible inputs (such as materials) respond freely and monotonically to the current productivity shock, such that they can be used as a proxy for productivity. This requires the absence of any constraints to material input use, such as credit constraints. A second assumption that control function estimators need to make for invertibility to hold is the absence of measurement error in inputs, specifically in materials.[18]

Control function estimators further require the researcher to make precise economic assumptions about the timing of input choices. Ackerberg, Caves, and Frazer (2015) discuss how different moment conditions can be constructed depending on the appropriate assumption about the timing of input choices. Their particular example is whether the choice of labour is predetermined or endogeneous; each assumption implies a different lag of labour in the moment conditions. In other words, different assumptions about the information set under which inputs are chosen lead to different valid moment conditions.

In our main implementation of the control function estimator, we follow the one-stage GMM estimation procedure developed by Wooldridge (2009). Specifically, we minimise the following set of moment conditions:

$$(\boldsymbol{z_{it1}} \quad \boldsymbol{z_{it2}}) \begin{pmatrix} y_{it} - \beta_0 - \beta_k k_{it} - \beta_l l_{it} - \beta_m m_{it} - \boldsymbol{c'_{it}\lambda} \\ y_{it} - \gamma_0 - \beta_k k_{it} - \beta_l l_{it} - \beta_m m_{it} - \boldsymbol{c'_{i,t-1}\lambda} \end{pmatrix}$$

where c_{it} are the elements of a third-order polynomial expansion in capital and materials which approximates the control function:

$$\begin{aligned} g(k_{it}, m_{it}) &= \boldsymbol{c'_{it}\lambda} \\ &= \lambda_0 + \lambda_1 k_{it} + \lambda_2 m_{it} + \lambda_3 k_{it}^2 + \lambda_4 m_{it}^2 + \lambda_5 k_{it} m_{it} + \lambda_6 k_{it}^3 + \lambda_6 m_{it}^3 + \lambda_7 k_{it}^2 m_{it} + \lambda_8 k_{it} m_{it}^2 \end{aligned}$$

and the instruments are given by:

$$\begin{aligned} \boldsymbol{z_{it1}} &= (1, k_{it}, l_{it}, m_{it}, l_{i,t-1}, m_{i,t-1}, c_{i,t}, c_{i,t-1}) \\ \boldsymbol{z_{it2}} &= (k_{it}, l_{i,t-1}, m_{i,t-1}, c_{i,t-1}) \end{aligned}$$

Our set of instruments is valid under the assumption that capital is predetermined, and labour and materials are endogenous to the current-period productivity shock.

As a robustness check, we implement and report the two-step procedure in Ackerberg, Caves, and Frazer (2015) in column (8) of Tables A.1 and A.4.

[18] Linear panel methods are robust to the presence of measurement error in inputs. This reflects the general property of instrumental variables estimators to be robust to measurement error which would otherwise cause attenuation bias.

Online Appendix Tables and Figures

Table A.1: **Production functions: Alternative specifications (Sri Lanka)**

Specification:	(1) OLS (no lag)	(2) OLS (with lag)	(3) FE (no lag)	(4) FE (with lag)	(5) Blundell-Bond (more IVs)	(6) Blundell-Bond (with lags)	(7) Blundell-Bond (lags; more IVs)	(8) Ackerberg-Caves-Frazer
Log capital	0.11***	0.04***	0.15***	0.13***	0.11*	0.26*	0.12	0.06**
	(0.02)	(0.01)	(0.03)	(0.03)	(0.06)	(0.15)	(0.10)	(0.03)
Log labour	0.21***	0.12***	0.10***	0.09***	0.20**	0.15	0.12	0.08
	(0.03)	(0.02)	(0.03)	(0.03)	(0.08)	(0.12)	(0.11)	(0.12)
Log materials	0.62***	0.40***	0.37***	0.34***	0.45***	0.53***	0.47***	0.71***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.08)	(0.06)	(0.04)
L.Log revenue		0.45***		0.14***	0.29***	0.40***	0.44***	
		(0.02)		(0.02)	(0.07)	(0.09)	(0.08)	
L.Log capital						-0.10	0.00	
						(0.13)	(0.09)	
L.Log labour						0.03	0.03	
						(0.05)	(0.05)	
L.Log materials						-0.13***	-0.10**	
						(0.05)	(0.05)	
Observations	3036	2629	3033	2626	2629	2512	2512	2505
Microenterprises	385	382	382	379	382	378	378	385
Hansen (p-value)					0.53	0.82	0.83	
AR(1) (p)					0.00	0.00	0.00	
AR(2) (p)					0.95	0.78	0.67	
Instruments					115	79	115	
Common factor (p)						0.00	0.00	
Underidentification (p-values):								
Log capital					0.02	0.34	0.20	
Log labour					0.03	0.08	0.28	
Log materials					0.01	0.00	0.02	
L.Log revenue					0.00	0.00	0.02	
L.Log capital						0.03	0.07	
L.Log labour						0.01	0.07	
L.Log materials						0.00	0.01	

Note: Estimators employed are OLS, firm fixed effects, Blundell and Bond (1998) System GMM and the Wooldridge (2009) implementation of Ackerberg, Caves, and Frazer (2015). All models include wave dummies (not reported). We report p-values for the Hansen (1982) test of over-identifying restrictions, the Arellano and Bond (1991) autocorrelation test, test of common factor restrictions in models with lagged inputs, and the Windmeijer (2018) test of instrument informativeness. Data are from Sri Lanka. Samples are equivalent to the preferred sample in the original study. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table A.2: **Production function: Separate by treatment (Sri Lanka)**

Specification:	(1) Splitting all	(2) Splitting capital	(3) Splitting labour	(4) Splitting all	(5) Splitting capital & materials
Log capital × Treated	0.06	0.12*			0.11
	(0.07)	(0.07)			(0.07)
Log capital × Control	0.07	0.14			0.14*
	(0.11)	(0.09)			(0.09)
Log capital			0.11	0.12	
			(0.08)	(0.08)	
Log labour × Treated	0.17		0.26***		
	(0.11)		(0.09)		
Log labour × Control	0.10		0.28***		
	(0.16)		(0.10)		
Log labour		0.23**		0.27***	0.25***
		(0.09)		(0.09)	(0.10)
Log materials × Treated	0.46***			0.42***	0.42***
	(0.07)			(0.06)	(0.07)
Log materials × Control	0.43***			0.44***	0.41***
	(0.08)			(0.06)	(0.07)
Log materials		0.42***	0.43***		
		(0.06)	(0.06)		
L.Log revenue	0.32***	0.28***	0.26***	0.26***	0.28***
	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)
Observations	2629	2629	2629	2629	2629
Microenterprises	382	382	382	382	382
Hansen (p-value)	0.08	0.24	0.10	0.11	0.13
Equality by treatment (p)	0.92	0.76	0.71	0.43	0.43

Note: All specification utilise the Blundell and Bond (1998) System GMM estimator. All models include wave dummies (not reported). We report p-values for the Hansen (1982) test of over-identifying restrictions, and tes for the equality of treatments. Data are from Sri Lanka. Samples are equivalent to the preferred sample in the original study. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table A.3: **Production function: Separate by sector (Sri Lanka)**

Specification:	(1) Splitting all factors	(2) Splitting capital	(3) Splitting labour	(4) Splitting all	(5) Splitting capital & materials
Log capital × Trade	0.11	0.17*			0.12
	(0.08)	(0.09)			(0.08)
Log capital × Non-trade	0.20***	0.17***			0.15**
	(0.07)	(0.06)			(0.06)
Log capital			0.15**	0.13**	
			(0.07)	(0.06)	
Log labour × Trade	-0.05		-0.10		
	(0.12)		(0.20)		
Log labour × Non-trade	0.32***		0.31***		
	(0.10)		(0.12)		
Log labour		0.24***		0.17*	0.18**
		(0.08)		(0.09)	(0.08)
Log materials × Trade	0.56***			0.45***	0.46***
	(0.07)			(0.07)	(0.07)
Log materials × Non-trade	0.46***			0.46***	0.46***
	(0.07)			(0.07)	(0.07)
Log materials		0.47***	0.45***		
		(0.06)	(0.06)		
L.Log revenue	0.25***	0.24***	0.29***	0.29***	0.28***
	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)
Observations	2629	2629	2629	2629	2629
Microenterprises	382	382	382	382	382
Hansen (p-value)	0.62	0.51	0.19	0.21	0.63
Equality by treatment (p)	0.04	0.99	0.10	0.87	0.93

Note: All specification utilise the Blundell and Bond (1998) System GMM estimator. All models include wave dummies (not reported). We report p-values for the Hansen (1982) test of over-identifying restrictions, and test for the equality of treatments. Data are from Sri Lanka. Samples are equivalent to the preferred sample in the original study. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table A.4: **Production functions: Alternative specifications (Ghana)**

Specification:	(1) OLS (no lag)	(2) OLS (with lag)	(3) FE (no lag)	(4) FE (with lag)	(5) Blundell-Bond (more IVs)	(6) Blundell-Bond (with lags)	(7) Blundell-Bond (lags; more IVs)	(8) Ackerberg-Caves-Frazer
Log capital	0.08***	0.04***	0.09***	0.09***	0.16***	0.11*	0.11*	0.07***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)	(0.06)	(0.06)	(0.02)
Log labour	0.13***	0.11***	0.11***	0.09***	0.17***	0.17**	0.17**	0.05
	(0.03)	(0.02)	(0.03)	(0.03)	(0.05)	(0.07)	(0.07)	(0.11)
Log materials	0.67***	0.46***	0.44***	0.42***	0.44***	0.45***	0.45***	0.71***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.09)	(0.12)	(0.12)	(0.03)
L.Log revenue		0.38***		0.02	0.22***	0.27***	0.27***	
		(0.02)		(0.02)	(0.04)	(0.05)	(0.05)	
L.Log capital						-0.04	-0.04	
						(0.03)	(0.03)	
L.Log labour						0.01	0.01	
						(0.06)	(0.06)	
L.Log materials						-0.03	-0.03	
						(0.04)	(0.04)	
Observations	3253	3105	3219	3058	3105	2301	2301	2326
Microenterprises	779	770	745	723	770	720	720	793
Hansen (p-value)					0.46	0.20	0.20	
AR(1) (p)					0.00	0.00	0.00	
AR(2) (p)					0.26	0.75	0.75	
Instruments					58	57	57	
Common factor (p)								
Underidentification (p-values):								
Log capital					0.00	0.00	0.00	
Log labour					0.00	0.00	0.00	
Log materials					0.00	0.03	0.03	
L.Log revenue					0.00	0.00	0.00	
L.Log capital						0.00	0.00	
L.Log labour						0.00	0.00	
L.Log materials						0.00	0.00	

Note: Estimators employed are OLS, firm fixed effects, Blundell and Bond (1998) System GMM and the Wooldridge (2009) implementation of Ackerberg, Caves, and Frazer (2015). All models include wave dummies (not reported). We report p-values for the Hansen (1982) test of over-identifying restrictions, the Arellano and Bond (1991) autocorrelation test, test of common factor restrictions in models with lagged inputs, and the Windmeijer (2018) test of instrument informativeness. Data are from Ghana. Samples are equivalent to the preferred sample in the original study. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table A.5: **Production function: Separate by treatment (Ghana)**

Specification:	(1) Splitting all factors	(2) Splitting capital	(3) Splitting labour	(4) Splitting materials	(5) Splitting capital & materials
Log capital × Treated	0.07**	0.08**			0.06*
	(0.03)	(0.04)			(0.03)
Log capital × Control	0.10***	0.12***			0.13***
	(0.04)	(0.04)			(0.04)
Log capital			0.16***	0.17***	
			(0.04)	(0.04)	
Log labour × Treated	0.12*		0.20***		
	(0.07)		(0.06)		
Log labour × Control	0.15**		0.17***		
	(0.07)		(0.05)		
Log labour		0.14***		0.19***	0.15***
		(0.05)		(0.05)	(0.05)
Log materials × Treated	0.56***			0.41***	0.53***
	(0.06)			(0.08)	(0.06)
Log materials × Control	0.47***			0.38***	0.47***
	(0.08)			(0.10)	(0.08)
Log materials		0.47***	0.40***		
		(0.08)	(0.09)		
L.Log revenue	0.19***	0.20***	0.23***	0.24***	0.20***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	3105	3105	3105	3105	3105
Microenterprises	770	770	770	770	770
Hansen (p-value)	0.14	0.13	0.60	0.61	0.14
Equality by treatment (p)	0.62	0.45	0.38	0.35	0.29

Note: All specification utilise the Blundell and Bond (1998) System GMM estimator. All models include wave dummies (not reported). We report p-values for the Hansen (1982) test of over-identifying restrictions, and test for the equality of treatments. Data are from Ghana. Samples are equivalent to the preferred sample in the original study. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table A.6: **Production function: Separate by sector (Ghana)**

Specification:	(1) Splitting all factors	(2) Splitting capital	(3) Splitting labour	(4) Splitting materials	(5) Splitting capital & materials
Log capital × Trade	0.10**	0.12**			0.08*
	(0.04)	(0.05)			(0.05)
Log capital × Non-trade	0.10*	0.16***			0.12**
	(0.06)	(0.06)			(0.06)
Log capital			0.14***	0.14***	
			(0.04)	(0.04)	
Log labour × Trade	0.18**		-0.03		
	(0.07)		(0.20)		
Log labour × Non-trade	0.14**		0.26**		
	(0.07)		(0.11)		
Log labour		0.18***		0.16***	0.15***
		(0.05)		(0.05)	(0.05)
Log materials × Trade	0.52***			0.42***	0.51***
	(0.07)			(0.10)	(0.08)
Log materials × Non-trade	0.58***			0.53***	0.58***
	(0.10)			(0.10)	(0.11)
Log materials		0.49***	0.49***		
		(0.09)	(0.08)		
L.Log revenue	0.20***	0.21***	0.21***	0.22***	0.20***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	3105	3105	3105	3105	3105
Microenterprises	770	770	770	770	770
Hansen (p-value)	0.30	0.32	0.30	0.30	0.22
Equality by treatment (p)	0.92	0.51	0.33	0.37	0.56

Note: All specification utilise the Blundell and Bond (1998) System GMM estimator. All models include wave dummies (not reported). We report p-values for the Hansen (1982) test of over-identifying restrictions, and test for the equality of treatments. Data are from Ghana. Samples are equivalent to the preferred sample in the original study. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table A.7: **TFP effects: no baseline controls**

	(1) OLS	(2) Quantile (0.2)	(3) Quantile (0.4)	(4) Quantile (0.5)	(5) Quantile (0.6)	(6) Quantile (0.8)
A. Dependent variable: log(TFP) estimated using Blundell-Bond estimator						
Dummy: Treated	0.05*	0.00	0.06	0.06	0.08*	0.08**
	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	4777	4777	4777	4777	4777	4777
Microenterprises	1114	1114	1114	1114	1114	1114
B. Dependent variable: log(TFP) estimated using Wooldridge estimator						
Dummy: Treated	0.05*	0.06	0.07*	0.06	0.07*	0.06*
	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	4777	4777	4777	4777	4777	4777
Microenterprises	1114	1114	1114	1114	1114	1114
C. Dependent variable: log(revenue/hours worked)						
Dummy: Treated	0.03	-0.01	0.01	0.04*	0.04*	0.05*
	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)	(0.03)
Log(Capital/labour)	0.11***	0.03*	0.04***	0.06***	0.07***	0.11***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Log(Materials/labour)	0.63***	0.82***	0.80***	0.77***	0.74***	0.63***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Log labour	-0.06**	-0.01	-0.03	-0.04**	-0.06***	-0.11***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	4777	4777	4777	4777	4777	4777
Microenterprises	1114	1114	1114	1114	1114	1114

Note: This table reports the effect of treatment on TFP at different moments of the distribution, for microenterprises in Ghana and Sri Lanka. In Panel A, TFP is estimated using the Blundell and Bond (1998) System GMM estimator. In Panel B, TFP is estimated using the Wooldridge (2009) implementation of Ackerberg, Caves, and Frazer (2015). In panel C, the dependent variable is the standard measure of labor productivity. All regressions include wave-times-survey and industry-times-country fixed effects.

Table A.8: **TFP effects: Sri Lanka**

	(1) ANCOVA	(2) Quantile (0.2)	(3) Quantile (0.4)	(4) Quantile (0.5)	(5) Quantile (0.6)	(6) Quantile (0.8)
A. Dependent variable: log(TFP) estimated using Blundell-Bond estimator						
Dummy: Treated	0.08*	0.01	0.05	0.10**	0.10**	0.09*
	(0.04)	(0.06)	(0.06)	(0.05)	(0.04)	(0.05)
Observations	3036	3036	3036	3036	3036	3036
Microenterprises	385	385	385	385	385	385
B. Dependent variable: log(TFP) estimated using Wooldridge estimator						
Dummy: Treated	0.07*	0.00	0.06	0.11**	0.09**	0.08*
	(0.04)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)
Observations	3036	3036	3036	3036	3036	3036
Microenterprises	385	385	385	385	385	385
C. Dependent variable: log(revenue/hours worked)						
Dummy: Treated	0.07**	0.03	0.07**	0.08**	0.07**	0.07*
	(0.04)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)
Log(Capital/labour)	0.06***	-0.00	0.01	0.02	0.05*	0.09***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Log(Materials/labour)	0.56***	0.73***	0.71***	0.68***	0.65***	0.55***
	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)
Log labour	-0.13***	-0.09**	-0.09***	-0.09***	-0.13***	-0.16***
	(0.03)	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)
Observations	3036	3036	3036	3036	3036	3036
Microenterprises	385	385	385	385	385	385

Note: This table reports the effect of treatment on TFP at different moments of the distribution, for microenterprises in Sri Lanka only. In Panel A, TFP is estimated using the Blundell and Bond (1998) System GMM estimator. In Panel B, TFP is estimated using the Wooldridge (2009) implementation of Ackerberg, Caves, and Frazer (2015). In panel C, the dependent variable is the standard measure of labor productivity. All regressions include wave-times-survey and industry-times-country fixed effects; and control for baseline outcomes. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table A.9: **TFP effects: Ghana**

	(1) ANCOVA	(2) Quantile (0.2)	(3) Quantile (0.4)	(4) Quantile (0.5)	(5) Quantile (0.6)	(6) Quantile (0.8)
A. Dependent variable: log(TFP) estimated using Blundell-Bond						
Dummy: Treated	0.04	0.03	0.04	0.05	0.05	0.06
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Observations	3253	3253	3253	3253	3253	3253
Microenterprises	779	779	779	779	779	779
B. Dependent variable: log(TFP) estimated using Wooldridge estimator						
Dummy: Treated	0.04	0.01	0.02	0.05	0.08*	0.05
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
Observations	3253	3253	3253	3253	3253	3253
Microenterprises	779	779	779	779	779	779
C. Dependent variable: log(revenue/hours worked)						
Dummy: Treated	0.02	-0.00	0.00	0.03	0.04	0.06
	(0.04)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)
Log(Capital/labour)	0.10***	0.06***	0.06***	0.05***	0.08***	0.11***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Log(Materials/labour)	0.63***	0.72***	0.77***	0.77***	0.74***	0.62***
	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)
Log labour	-0.09***	-0.04	-0.02	-0.04	-0.05*	-0.11***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
Observations	3253	3253	3253	3253	3253	3253
Microenterprises	779	779	779	779	779	779

Note: This table reports the effect of treatment on TFP at different moments of the distribution, for microenterprises in Ghana only. In Panel A, TFP is estimated using the Blundell and Bond (1998) System GMM estimator. In Panel B, TFP is estimated using the Wooldridge (2009) implementation of Ackerberg, Caves, and Frazer (2015). In panel C, the dependent variable is the standard measure of labor productivity. All regressions include wave-times-survey and industry-times-country fixed effects; and control for baseline outcomes. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table A.10: TFP effects: Separate by gender (Sri Lanka)

	(1) ANCOVA	(2) Quantile (0.2)	(3) Quantile (0.4)	(4) Quantile (0.5)	(5) Quantile (0.6)	(6) Quantile (0.8)
A. Dependent variable: log(TFP) estimated using Blundell-Bond						
Dummy: Male × Treated	0.09*	0.09	0.11*	0.10*	0.07	0.09
	(0.05)	(0.09)	(0.06)	(0.05)	(0.06)	(0.06)
Dummy: Female × Treated	0.05	-0.07	0.01	0.08	0.11*	0.06
	(0.06)	(0.11)	(0.08)	(0.08)	(0.06)	(0.07)
Female	-0.17***	-0.09	-0.16***	-0.17***	-0.19***	-0.20***
	(0.05)	(0.07)	(0.06)	(0.05)	(0.06)	(0.05)
Observations	3036	3036	3036	3036	3036	3036
Microenterprises	385	385	385	385	385	385
Treatments equal (p)	0.60	0.24	0.31	0.82	0.62	0.78
Treatments zero (p)	0.17	0.47	0.24	0.14	0.12	0.31
B. Dependent variable: log(TFP) estimated using Wooldridge estimator						
Dummy: Male × Treated	0.09*	0.08	0.11*	0.09	0.07	0.08
	(0.05)	(0.09)	(0.06)	(0.05)	(0.05)	(0.06)
Dummy: Female × Treated	0.05	-0.08	0.01	0.05	0.11*	0.06
	(0.06)	(0.09)	(0.07)	(0.07)	(0.06)	(0.06)
Female	-0.16***	-0.08	-0.15***	-0.15***	-0.18***	-0.19***
	(0.05)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)
Observations	3036	3036	3036	3036	3036	3036
Microenterprises	385	779	779	779	779	779
Treatments equal (p)	0.61	0.19	0.29	0.67	0.62	0.83
Treatments zero (p)	0.20	0.42	0.20	0.25	0.09	0.24
C. Dependent variable: log(revenue/hours worked)						
Dummy: Male × Treated	0.08*	0.07	0.09*	0.09**	0.07*	0.08
	(0.05)	(0.06)	(0.04)	(0.05)	(0.04)	(0.05)
Dummy: Female × Treated	0.06	-0.01	0.04	0.08*	0.08*	0.02
	(0.05)	(0.07)	(0.04)	(0.04)	(0.05)	(0.05)
Female	-0.10**	-0.00	-0.02	-0.09*	-0.11***	-0.10**
	(0.04)	(0.06)	(0.04)	(0.04)	(0.04)	(0.05)
Observations	3036	3036	3036	3036	3036	3036
Microenterprises	385	385	385	385	385	385
Treatments equal (p)	0.81	0.40	0.44	0.79	0.88	0.36
Treatments zero (p)	0.14	0.54	0.12	0.04	0.07	0.31

Note: This table reports tests for heterogeneous effects by gender of treatment on productivity at different moments of the distribution, for microenterprises in Sri Lanka. In Panel A, TFP is estimated using the Blundell and Bond (1998) System GMM estimator. In Panel B, TFP is estimated using the Wooldridge (2009) implementation of Ackerberg, Caves, and Frazer (2015). In panel C, the dependent variable is the standard measure of labor productivity. All regressions include wave and industry dummies, a gender dummy; and control for baseline outcomes. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table A.11: TFP effects: Separate by gender (Ghana)

	(1) ANCOVA	(2) Quantile (0.2)	(3) Quantile (0.4)	(4) Quantile (0.5)	(5) Quantile (0.6)	(6) Quantile (0.8)
A. Dependent variable: log(TFP) estimated using Blundell-Bond						
Dummy: Male × Treated	0.01	-0.07	-0.04	0.01	0.01	0.01
	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	(0.08)
Dummy: Female × Treated	0.04	-0.04	0.03	0.05	0.05	0.10
	(0.05)	(0.06)	(0.04)	(0.05)	(0.05)	(0.06)
Female	-0.13***	-0.07**	-0.08**	-0.07**	-0.06	-0.14***
	(0.05)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)
Observations	3142	3142	3142	3142	3142	3142
Microenterprises	753	385	385	385	385	385
Treatments equal (p)	0.64	0.75	0.28	0.62	0.55	0.34
Treatments zero (p)	0.75	0.47	0.55	0.56	0.64	0.33
B. Dependent variable: log(TFP) estimated using Wooldridge estimator						
Dummy: Male × Treated	0.01	-0.06	-0.04	-0.00	0.01	0.06
	(0.06)	(0.08)	(0.06)	(0.05)	(0.07)	(0.08)
Dummy: Female × Treated	0.04	-0.02	0.04	0.04	0.06	0.15**
	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.07)
Female	-0.16***	-0.08**	-0.11***	-0.08**	-0.09**	-0.16***
	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)	(0.06)
Observations	3142	3142	3142	3142	3142	3142
Microenterprises	753	779	779	779	779	779
Treatments equal (p)	0.60	0.67	0.25	0.51	0.45	0.37
Treatments zero (p)	0.65	0.69	0.50	0.71	0.38	0.12
C. Dependent variable: log(revenue/hours worked)						
Dummy: Male × Treated	0.02	-0.01	0.00	0.00	0.01	0.04
	(0.06)	(0.07)	(0.05)	(0.05)	(0.06)	(0.07)
Dummy: Female × Treated	0.06	0.00	0.02	0.04	0.04	0.12**
	(0.05)	(0.06)	(0.04)	(0.04)	(0.05)	(0.06)
Female	-0.13**	-0.02	-0.08*	-0.09**	-0.10**	-0.13**
	(0.05)	(0.06)	(0.05)	(0.04)	(0.04)	(0.06)
Observations	3142	3142	3142	3142	3142	3142
Microenterprises	753	385	385	385	385	385
Treatments equal (p)	0.64	0.95	0.68	0.47	0.59	0.31
Treatments zero (p)	0.49	1.00	0.83	0.62	0.68	0.09

Note: This table reports tests for heterogeneous effects by gender of treatment on productivity at different moments of the distribution, for microenterprises in Ghana. In Panel A, TFP is estimated using the Blundell and Bond (1998) System GMM estimator. In Panel B, TFP is estimated using the Wooldridge (2009) implementation of Ackerberg, Caves, and Frazer (2015). In panel C, the dependent variable is the standard measure of labor productivity. All regressions include wave and industry dummies, a gender dummy; and control for baseline outcomes. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table A.12: TFP effects: Separate by treatment (Ghana)

	(1) ANCOVA	(2) Quantile (0.2)	(3) Quantile (0.4)	(4) Quantile (0.5)	(5) Quantile (0.6)	(6) Quantile (0.8)
A. Dependent variable: log(TFP) estimated using Blundell-Bond						
Dummy: Cash	-0.00	0.01	-0.02	-0.01	-0.03	0.04
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)
Dummy: Equip	0.08	0.06	0.10	0.12*	0.12**	0.07
	(0.05)	(0.06)	(0.07)	(0.07)	(0.05)	(0.07)
Observations	3253	3253	3253	3253	3253	3253
Microenterprises	779	779	779	779	779	779
Treatments equal (p)	0.21	0.53	0.09	0.08	0.04	0.70
Treatments zero (p)	0.30	0.59	0.21	0.18	0.05	0.55
B. Dependent variable: log(TFP) estimated using Wooldridge estimator						
Dummy: Cash	-0.00	-0.01	-0.00	-0.03	0.01	0.04
	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.07)
Dummy: Equip	0.08	0.02	0.10*	0.10*	0.13**	0.07
	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)
Observations	3253	3253	3253	3253	3253	3253
Microenterprises	779	779	779	779	779	779
Treatments equal (p)	0.16	0.62	0.12	0.06	0.11	0.71
Treatments zero (p)	0.23	0.88	0.18	0.14	0.04	0.54
C. Dependent variable: log(revenue/hours worked)						
Dummy: Cash	-0.01	-0.04	-0.02	-0.00	-0.01	0.05
	(0.05)	(0.06)	(0.04)	(0.04)	(0.04)	(0.06)
Dummy: Equip	0.06	0.02	0.04	0.07*	0.06	0.07
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)
Observations	3253	3253	3253	3253	3253	3253
Microenterprises	779	779	779	779	779	779
Treatments equal (p)	0.20	0.33	0.29	0.11	0.09	0.75
Treatments zero (p)	0.37	0.62	0.56	0.17	0.18	0.36

Note: This table reports the effect of cash and in-kind treatment on TFP at different moments of the distribution, for microenterprises in Ghana only. In Panel A, TFP is estimated using the Blundell and Bond (1998) System GMM estimator. In Panel B, TFP is estimated using the Wooldridge (2009) implementation of Ackerberg, Caves, and Frazer (2015). In panel C, the dependent variable is the standard measure of labor productivity. All regressions include wave-times-survey and industry-times-country fixed effects; and control for baseline outcomes. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table A.13: TFP effects: Separate by treatment (Sri Lanka)

	(1) ANCOVA	(2) Quantile (0.2)	(3) Quantile (0.4)	(4) Quantile (0.5)	(5) Quantile (0.6)	(6) Quantile (0.8)
A. Dependent variable: log(TFP) estimated using Blundell-Bond						
Dummy: Cash	0.11*	-0.01	0.08	0.14**	0.12**	0.12*
	(0.06)	(0.08)	(0.07)	(0.06)	(0.06)	(0.07)
Dummy: Equip	0.05	0.02	0.04	0.06	0.07	0.03
	(0.05)	(0.10)	(0.07)	(0.06)	(0.05)	(0.05)
Observations	3036	3036	3036	3036	3036	3036
Microenterprises	385	385	385	385	385	385
Treatments equal (*p*)	0.45	0.78	0.63	0.25	0.41	0.23
Treatments zero (*p*)	0.16	0.96	0.57	0.06	0.08	0.17
B. Dependent variable: log(TFP) estimated using Wooldridge estimator						
Dummy: Cash	0.10*	-0.00	0.07	0.14**	0.11*	0.13**
	(0.06)	(0.07)	(0.08)	(0.06)	(0.05)	(0.06)
Dummy: Equip	0.05	0.00	0.05	0.07	0.07	0.04
	(0.05)	(0.09)	(0.06)	(0.05)	(0.05)	(0.05)
Observations	3036	3036	3036	3036	3036	3036
Microenterprises	385	385	385	385	385	385
Treatments equal (*p*)	0.48	0.98	0.84	0.30	0.51	0.22
Treatments zero (*p*)	0.18	1.00	0.56	0.06	0.11	0.14
C. Dependent variable: log(revenue/hours worked)						
Dummy: Cash	0.09*	0.00	0.08*	0.10**	0.11**	0.10**
	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Dummy: Equip	0.06	0.06	0.04	0.06	0.05	0.03
	(0.04)	(0.06)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	3036	3036	3036	3036	3036	3036
Microenterprises	385	385	385	385	385	385
Treatments equal (*p*)	0.57	0.32	0.42	0.46	0.25	0.16
Treatments zero (*p*)	0.13	0.46	0.15	0.08	0.05	0.12

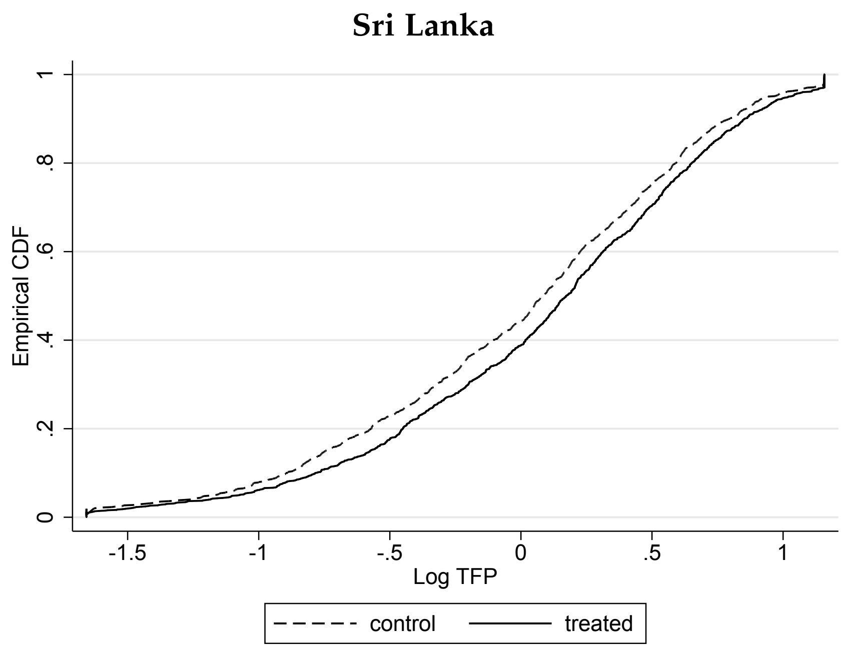
Note: This table reports the effect of cash and in-kind treatment on TFP at different moments of the distribution, for microenterprises in Ghana only. In Panel A, TFP is estimated using the Blundell and Bond (1998) System GMM estimator. In Panel B, TFP is estimated using the Wooldridge (2009) implementation of Ackerberg, Caves, and Frazer (2015). In panel C, the dependent variable is the standard measure of labor productivity. All regressions include wave-times-survey and industry-times-country fixed effects; and control for baseline outcomes. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

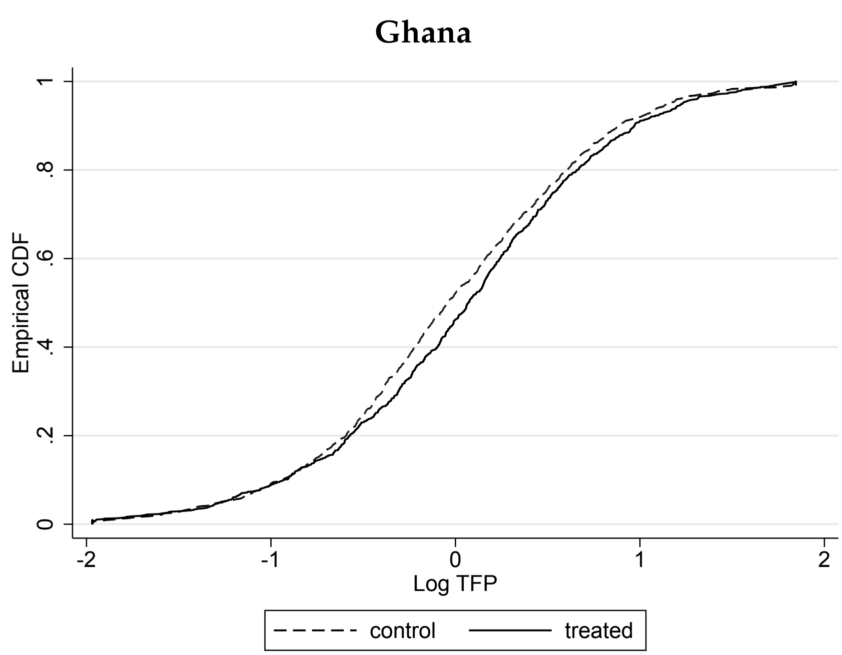
Table A.14: **Effects of grants on capital: intensive and extensive margin by category**

	(1) Total	(2) Tools	(3) Machinery	(4) Furniture	(5) Vehicles	(6) Other
A. Total value of assets						
Dummy: Treated	3594.79***	657.41**	100.32	-64.15	526.10**	2107.95***
	(961.61)	(321.47)	(565.24)	(107.61)	(224.37)	(568.90)
Control mean	15,555	2,538	7,197	1,809	584	3,179
Observations	3,341	3,341	3,333	3,358	3,345	3,345
Microenterprises	385	385	385	385	385	385
B. Total value of higher-technology assets						
Dummy: Treated	2814.05***	182.50	244.97	0.00	426.08**	2026.89***
	(892.88)	(219.12)	(512.25)	(.)	(211.49)	(560.07)
Control mean	10,838	433	6,864	0	273	2,920
Observations	3,341	3,341	3,333	3,358	3,345	3,345
Microenterprises	385	385	385	385	385	385
B. Ownership of higher-technology assets						
Dummy: Treated	0.08***	0.03	0.01	0.00	0.03**	0.09***
	(0.03)	(0.02)	(0.02)	(.)	(0.01)	(0.02)
Control Mean	0.61	0.13	0.33	0	0.02	0.25
Observations	3,358	3,358	3,358	3,358	3,358	3,358
Microenterprises	385	385	385	385	385	385

Note: This table provides an additional breakdown of the effect of capital grants on microenterprise capital in Sri Lanka. Categories of assets are as defined in DMW's questionnaire. Technology component of assets is coded according to our specifications in the text. No item within the furniture category is coded as higher-technology. Asset ownership is a dummy whether any item within a category is owned by the microenterprise. All regressions include baseline values of the dependent variable and control for wave dummies. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

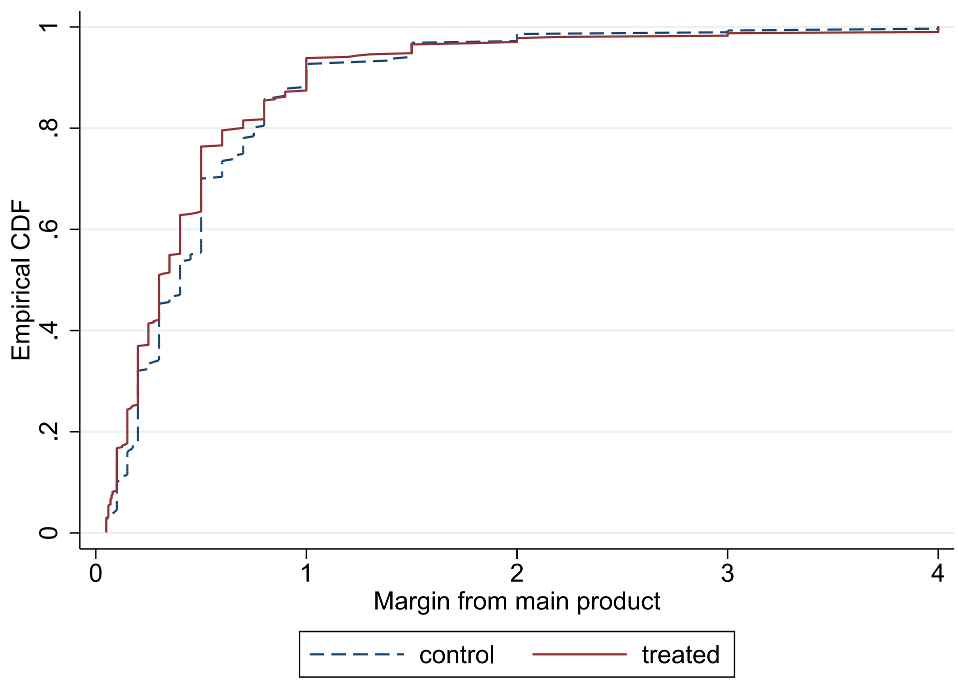
Figure A.1: **Capital grant treatment effects on productivity**





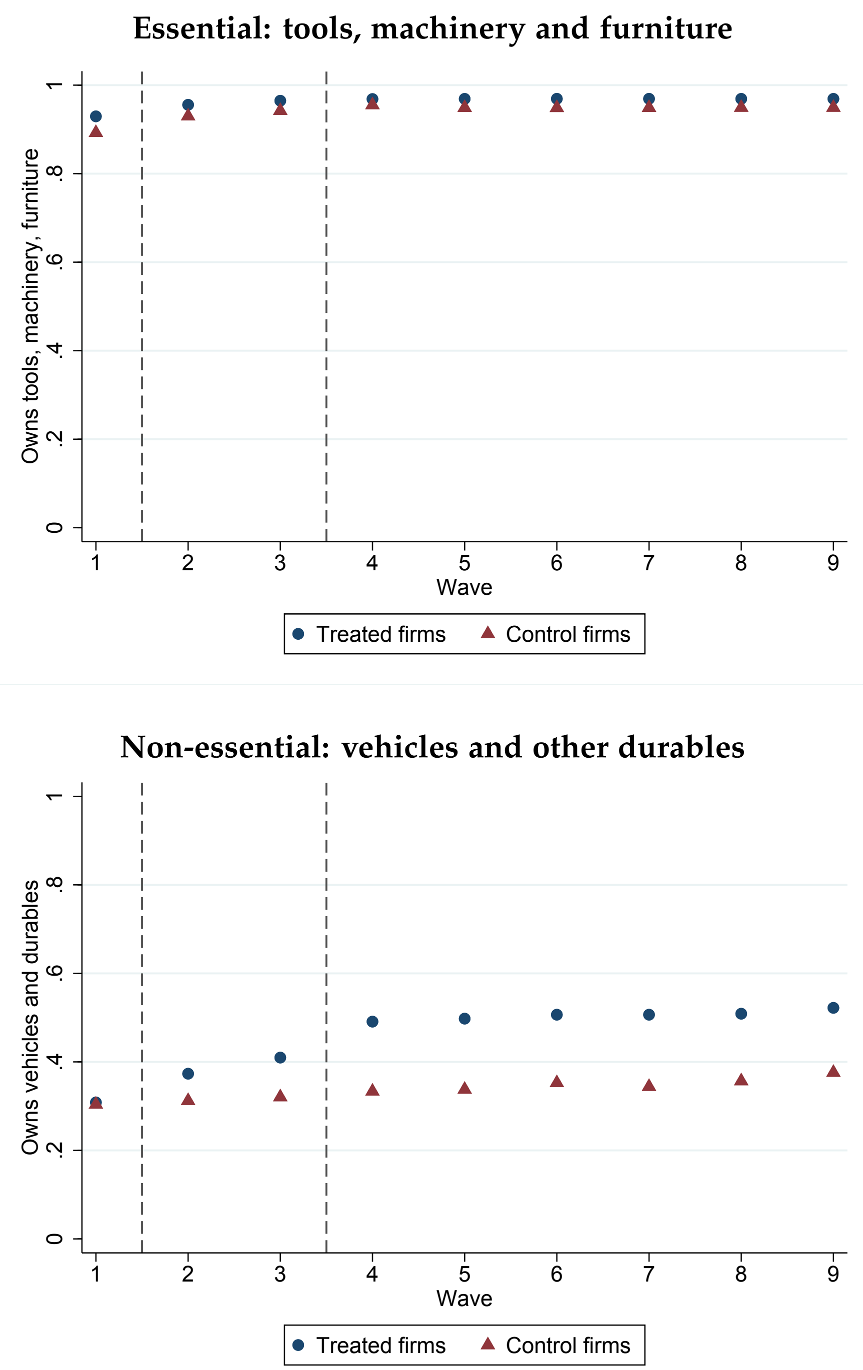
Note: CDFs of TFP for treated and untreated microenterprises in the waves after treatment was administered. Wilcoxon rank-sum test of equality of distribution p-values: 0.07 (Sri Lanka) and 0.01 (Ghana).

Figure A.2: Effects on sales margins



Note: CDFs of sales margins for the most important product, separate by treatment and control. Data from Sri Lanka, survey waves 7 and 8. Wilcoxon rank-sum test of equality of distribution p-values: 0.0196.

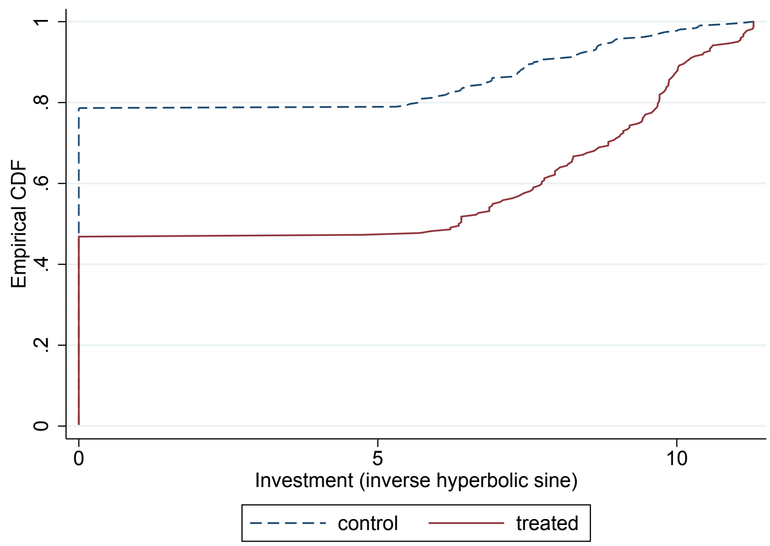
Figure A.3: **Ownership of fixed assets: Treatment and control by wave**



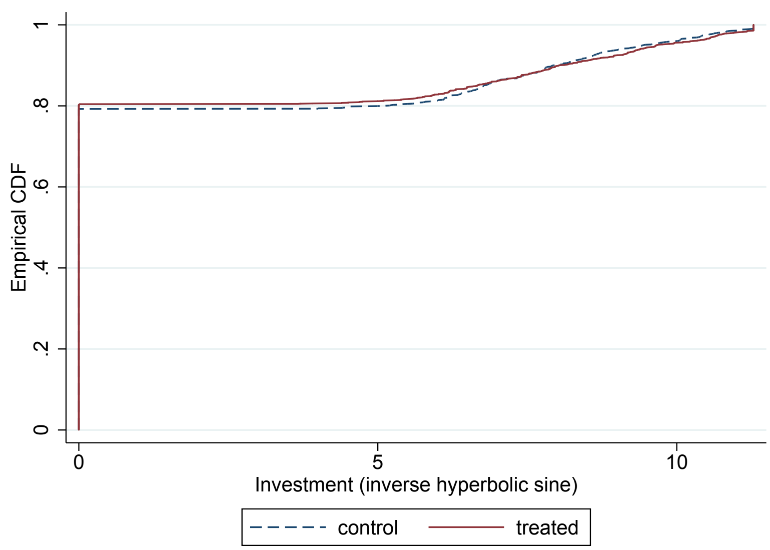
Note: This figure shows the share of treatment and control firms that own assets in different categories. Tools, machinery and furniture are owned by almost all microenterprises and are therefore labelled 'essential'. Vehicles and other durables are owned by a smaller fraction of microenterprises, and increase significantly in the treatment as opposed to the control group. The intervention window lies between the two vertical lines.

Figure A.4: Investments upon treatment and follow-up investments

(a) CDF of investment upon treatment

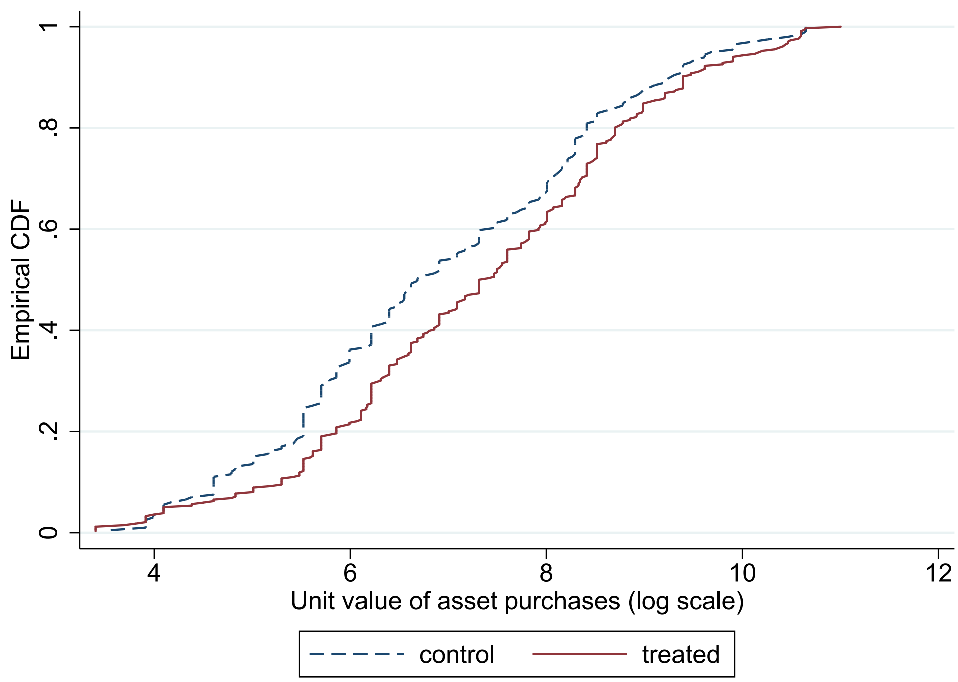


(b) CDF of follow-up investment



Note: Figure shows CDF of investment (after inverse hyperbolic sine transformation) in fixed capital for treated and control firms, in Sri Lanka. Top figure (a) shows investment in the waves immediately after the capital grants (waves 2 and 4). Bottom figure shows investment in subsequent waves (waves 3-9 for the early treatment group, and waves 5-9 for the late treatment group). Wilcoxon rank-sum test: $p < 0.001$ (top panel), $p = 0.572$ (bottom panel).

Figure A.5: Unit value of new asset purchases



Note: CDFs unit value of new fixed assets microenterprises purchased by treated and untreated firms in Sri Lanka. Excludes initial asset stock listed in baseline survey. Wilcoxon rank-sum test of equality of distribution p-values = 0.0067.