Do capital grants improve microenterprise productivity?*

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Abstract

Do capital grants improve microenterprise productivity? We use the lens of a production function to re-examine two previous randomised controlled trials that allocated capital 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. Although long-run estimates are noisy, point estimates indicate that these productivity effects are sustained six years after the grants. We explore possible mechanisms for this finding, and show that treatment tilts the asset composition towards durables with a higher technology component: a result consistent with a important role for capital-embodied technology. Mediation analysis confirms that virtually all of the effect of treatment on productivity can be explained by the adoption of higher-technology durables.

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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 (Blundell and Bond, 1998), a control function estimator (Wooldridge, 2009), and an estimator exploiting the firm's first-order condition (Gandhi, Navarro, and Rivers, 2020).

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 6 and 29 percent of the increase in revenue caused by capital grants can be attributed directly to an increase in productivity in Sri Lanka, and between 21 and 40 percent in Ghana – over and above adjustments of production factors. For Sri Lanka, where follow-up data are available to us for up to six years after the treatment, long-run point estimates – even though very noisy – suggest that productivity increases are sustained in the long term, putting firms on a different growth path.

Building on this first result, we examine the mechanisms through which capital grants affect TFP. One plausible mechanism is that treatment introduced advanced equipment and thus more efficient means of production to the firm. We exploit the richness of the asset data collected by DMW in Sri Lanka to test for this mechanism. We find that treated firms invest their grants unevenly: they particularly acquire assets that are not essential to the core activities of a business, but rather assets that can be used to run such activities more efficiently. Assets acquired by treated firms also have a relatively higher technology component. In contrast, treatment does not increase ownership or value of capital that most firms already used at baseline – such as tools, machinery and furniture – and has only a small effect on low-technology assets. Beyond a short-lived initial hoarding of inventories immediately upon receiving the grants, treatment also does not sustainably affect the stock of materials and goods held by firms. The change in the asset composition further changes the way firms do business. Treated businesses expand their customer base, and reach wider market segments through new and different products, facilitated by the acquisition of assets to produce or handle those products.

Finally, we formally test whether the adoption of different types of capital is the mechanism that explains the productivity effects of capital grants. We perform a formal mediation analysis and estimate the 'Average Controlled Direct Effect' (ACDE) proposed by Acharya, Blackwell, and Sen (2016). We find, across different production function estimators, that close to 100% of the treatment effect on productivity is driven by the tilt in the capital composition towards assets with a higher technology component, and assets that were less essential to core business activities at baseline. This suggests that the increase in overall productivity due to capital grants is embodied in certain types of capital that firms adopted.

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. A large literature has documented that low-productivity, mostly informal, microenterprises dominate this firm size distribution in developing countries, with adverse consequences for aggregate productivity (Hsieh and Klenow, 2009). It has proved difficult, in practice, either to reallocate economic activities out of this sector (Koelle, 2019; Ulyssea, 2018; La Porta and Shleifer, 2014; de Andrade, Bruhn, and McKenzie, 2014), or to improve directly the productivity of microenterprises (Bruhn et al., 2018; Atkin et al., 2017; Karlan, Knight, and Udry, 2015; McKenzie and Woodruff, 2014).

We show that capital grants – a policy not targeted at or thought to improve productivity – can have such an effect, if they succeed in introducing more advanced and productive capital equipment to firms. In order to show this, and because productivity cannot be measured directly in the data, we apply standard methods for productivity 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; Gandhi et al., 2020) which have previously only been applied to large firms with detailed and sophisticated accounting practices and financial records.[1] We show that, with high-quality panel data, these can be usefully applied to informal microenterprises, given the consistency across all tested estimators. This enables us to test how an intervention affects microenterprise productivity.

Second, we show that capital-embodied technology is a key mechanism behind the productivity increase that we document. The idea of capital-embodied technology dates to the early models of capital vintage by Johansen (1959) and Solow (1959). Griliches (1979) 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.[2]

Our evidence for this mechanism comes from a set of firms where the production technology and the capital stock are very simple – and therefore transparent and easy to understand. We observe the name and value of each individual capital asset, allowing us to distinguish between assets of different technology content and functional role in the firm. 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 et al., 2017; Karlan et al., 2015; Bloom, Eifert, Mahajan, McKenzie, and Roberts, 2013; Conley and Udry, 2010).

Together, our results have several key implications for understanding microenterprises in low-income settings. If capital grants impact such enterprises exclusively through a capital channel, this tends to imply (i) that there are diminishing marginal returns to scale in the provision of such grants (implied directly by the diminishing marginal return to capital in standard firm production functions), (ii) that capital grants are likely to have transitory impacts (with recipient microenterprises converging back to their steady state, as in the model in FMQW), and (iii) that there should be a categorical distinction between policies design to encourage technological upgrading in small firms (including, for example, through mentoring or management training) and policies designed to support capital accumulation (such as grants and loans). In contrast, our results – that capital

[1] The only exceptions we are aware of are Atkin et al. (2017), Atkin, Khandelwal, and Osman (2019) and Keniston (2011), who estimate microenterprise production functions using control function methods (Levinsohn and Petrin, 2003; Ackerberg, Caves, and Frazer, 2015).

[2] Several earlier qualitative studies report that owners of small firms identify technology as an important constraint of productivity and expansion (Aftab and Rahim, 1989; Kabecha, 1998). By contrast, access to better intermediate inputs in production has been recognised in the economic literature as a channel for productivity gains from trade (Amiti and Konings, 2007; Halpern, Koren, and Szeidl, 2015).

transfers facilitate a TFP effect, through upgrading to higher-technology durables – challenge each of these implications. Specifically, our results imply (i) that there is likely to be a local convexity in returns to capital transfers (in the sense that lumpy grants, of the kind studied in Sri Lanka and in Ghana, facilitate a discrete shift in capital type), (ii) the effects of lumpy capital grants are likely to be highly persistent (de Mel, McKenzie, and Woodruff, 2012), and (iii) policy should think about capital transfers – whether through grants or through loans – as itself encouraging technological upgrading and growth in small firms. We expand upon these implications in the conclusion to this paper.

Our paper proceeds as follows. Section 2 describes the experiments and data. We outline our identification strategy for TFP estimates in section 3, and present results on productivity in section 4. Section 5 provides evidence on mechanisms, and 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 et al. (2008). It spans a representative sample of 383 microenterprises, with a capital stock of less than 100,000 LKR (about $1000), in the manufacturing, retail and service sectors. Firms with a capital stock up to this value were chosen to ensure that the grant would represent a significant shock relative to their existing stock. The sample was taken in three districts, which were chosen for a high share of own-account workers and modest education levels. Numerous firms in the baseline survey were affected by the 2004 tsunami and were subsequently excluded from the sample. About 30% of the sample are engaged in artisanal food and clothing manufacturing, another 30% are retail shops, 15% work in services (mostly repairs) and the remainder are engaged in a variety of specialised trade and manufacturing activities. Owners are self-employed and have no paid employees. We mainly use the first nine waves of the data; these are equally spaced, three months apart. The first wave started in April 2005.

After the first 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 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. In the baseline survey, firm owners were asked about which item would increase profits the most (independent of cost). These average LKR 25,000 and 43% were

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

below LKR20,000 indicating that the treatment amounts were economically significant. A total of 124 firms received treatment after wave 1, and another 104 after wave 3. The probability of treatment was equal in each district. The grants were framed as a random prize draw to compensate for participation in the survey, and were only announced to firms in the wave in which it was received. 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. Only a few firms spent less than the treatment amount, while two-thirds of owners contributed (mostly trivial) additional funds to the purchase. Approximately 57% of the goods purchased were inventories or raw materials, 39% machinery or equipment, and 4% were construction materials for buildings. Cash grants were explicitly given without restrictions and enumerators noted that owners could purchase anything they want. Approximately 58% of grants were invested in the firm, while 12% was saved and the remainder used on loan repayments, household expenditures, house repairs and other items. 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, about 40% and 17% of the cash grants were spent on the purchase of inventories and equipment respectively.

The Ghana Microenterprise Survey was collected for the work of Fafchamps et al. (2014). FMQW surveyed 793 microenterprises (479 with female owners and 214 with male), without paid employees or a motorised vehicle, in Accra and the neighbouring port town of Tema. These firms operate in similar sectors as those in Sri Lanka and were small enough so that the treatment would be economically significant. About 40% are traders, about a third are engaged in artisanal food an clothing manufacturing, and the remainder work in service occupations such as repairs or beauty salons. A significant difference in the Ghana is the much higher labour-force participation rate of women. As 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]

The experimental design in FMQQ mostly replicated that of Sri Lanka; however, the design used a more detailed stratification, to improve power and balance over simple randomisation. The sample is stratified by sector, gender, baseline capital stock, and a binary variable measuring potential capture of cash or firm profits by family members. Within each strata, four firms with similar firm profits were grouped. Within each quadruplet, two firms were allocated grants, and the other two remained control firms. Capital grants were randomly allocated after the second and the third wave; and for a small group, after the fourth wave. Grants were again framed as randomly drawn prices to compensate for participation in the survey. Two treatment groups of 198 firms each received cash and in-kind grants respectively, leaving a control group of 396 firms. The grant size was GHC 150, or about $120 – and, and unlike in Sri Lanka, there was no

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

variation in the grant size. The grants are comparable in size to the smaller grants in Sri Lanka. They amount to two months of median baseline profits (median baseline profits were 68 GHC). The grant size was small enough that both purchased inventories and equipment could be liquidated easily. Since the firms in Ghana are less capital-intensive than in Sri Lanka, grants constituted a relatively larger shock to the capital stock, and almost doubled median baseline capital of GHC 170. The majority of in-kind grants were chosen in the form of inventories and materials. Only 24% of participants chose to buy physical equipment (including sewing machines, hair dryers, and carpentry tools).

Several features of the data make them particularly suitable to estimate the effects of capital grants on productivity, and to test the mechanism of capital-embedded productivity growth in a micro setting. First, the details of the production process, the nature of capital, and the boundaries of the firm are well understood. In comparison to large, often transnational enterprises in advanced economies, the difficulties arising from multi-product and multi-establishment firms, the role of intangible capital or strategic accounting practices, and price mark-ups created by product market power, are much reduced (Atkin et al., 2019). Second, both surveys advanced the measurement of business concepts for microenterprises, which were thought to be very challenging to enumerate given the absence of formal accounting systems or often even written records (De Mel, McKenzie, and Woodruff, 2009; Fafchamps, McKenzie, Quinn, and Woodruff, 2012). We use self-reported headline profits and sales, which give the most accurate measurement (De Mel et al., 2009). Capital is directly reported item-by-item at baseline, and additions, improvements, damages and sales are recorded at each follow-up wave. Unlike many empirical studies of large firms, imputation of capital is therefore not required. Third, the coverage of inputs and outputs (capital, labour, intermediate goods stocks and flows, sales, and profits) is comprehensive. The rate of missing data on inputs is low. Most frequently missing is capital, for 7% of firms in each wave in Sri Lanka and 10% in Ghana, on average.[5] This compares favourably with ORBIS and similar databases on large enterprises in developed countries.[6] Fourth, the survey instruments as well as the main experimental design are very similar across the two contexts; allowing us to test our hypotheses in two very different yet comparable contexts. We discuss further details on the construction of variables for our analysis in Appendix A.

[5] Appendix Table A.1 tests for differential attrition as well as for differential non-response on the production function variables (output and inputs). Besides a standard test for differential attrition by treatment status, we additionally test whether attrition differs along the firm productivity distribution. For example, high productivity firm might be less likely to drop out, which could lead us to overstate the true treatment effect. Our results indicate that overall, non-response and attrition do not systematically relate to treatment status and firm productivity. However, there is some weak evidence (marginally significant and quantitatively small) that in Ghana treated firms were slightly less likely to have missing data. Because of this, we perform a Lee (2009) bounding exercise as part of our robustness checks (Appendix Table A.22).

[6] See, for example, Table 9 in Maffini and Mokkas (2011), discussing missing data problems in ORBIS.

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 keep this discussion of widely used methods at a general level, but provide a more technical review in Appendix B.

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.[7] Further, we specify Y_{it} in revenue terms.[8]

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 $\log(A_{it}) \equiv \gamma_t + \omega_{it} + v_{it}$. 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 all firms; (ii) ω_{it}, a time-variant, firm-specific shock that 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); Gandhi et al. (2020)).[9]

[7] The alternative would be to denote Y_{it} as value added. In a value-added production function, the contribution of the intermediate inputs is netted out and the production of value added is specified 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, 2017); however, we do not view that as a reasonable restriction for this context.

[8] That is, we estimate TFPR rather than TFPQ. As Atkin et al. (2019) explain, "if a firm's capabilities come from its ability to produce both quality and quantity, TFPR may be closer to the object of interest even though it confounds forces unrelated to productivity."

[9] The dynamic linear panel approach discussed below – but not the control function methods – additionally accommodates firm-level fixed effects by applying first-differencing to the the data. Gandhi et al. (2020)'s preferred implementation of their estimator, which we follow here, does not include firm fixed effects. Given that we do not find substantial differences in the TFP estimates between alternative models, the inclusion or exclusion of such fixed effects seems not to be critical for our results and conclusions.

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 et al. (2020)). Three standard approaches to overcome transmission bias are (i) to estimate the production function from equation 2) in a dynamic linear panel framework, (ii) to specify a control function for productivity, or – most recently – (iii) to exploit the first-order condition implied by the firm's optimisation problem.

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). As in the standard linear panel estimation of production functions, we begin by taking first differences, to remove firm fixed effects (see, for example, Blundell and Bond (2000)). 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.[10]

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 (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009).[11] 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. Recently, Ackerberg et al. (2015) have identified a functional dependence problem in the early class of control function estimators such as (Olley and Pakes, 1996; Levinsohn and Petrin, 2003). We implement the Wooldridge (2009) implementation of the control function approach, which is robust to such functional dependence concerns.

A third approach – proposed by Gandhi et al. (2020) (GNR henceforth) – responds to the concern that flexible inputs (materials, electricity, etc.) are not adequately identified in the above structural estimators, because the invertibility assumption may not hold. To solve this, GNR develop an empirical strategy that, relying on the first order conditions of the firm, nonparametrically identifies the flexible input elasticity. This solves for the missing source of identification for the production function within a proxy variable

[10] Indeed, the identification of a linear production function estimator relies on adjustment costs or other optimisation frictions: Bond and Söderbom (2005); Shenoy (2018); Gandhi et al. (2020).

[11] Ackerberg et al. (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.

structure. Within the context of informal firms, one might, on conceptual grounds, expect measurement error and financial constraints to pose a challenge to invertibility. We therefore also apply this estimator, using our Cobb-Douglas specification.

We implement all of these approaches in our setting. 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 are robust to a wide range of commonly used productivity estimators.

To implement these estimators in the context of experimental data from microenterprises in developing countries, we make some technical adjustments. First, for power reasons, we pool data from treatment and control firms. To account for the effects of treatment on the variables in the production function, we partial out treatment and time effects from output and inputs before they enter the production function estimation, by taking the residual of a regression of each variable on treatment and time dummies.[12] Second, to reduce the influence of outliers that are due to measurement error, we winsorize each input at the top and bottom 1%. Third, we restrict the sample to firms with strictly positive amounts of all inputs, including capital. Finally, we deflate monetary values with the CPI in each country.

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 4, 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 these in more detail. In columns 2 and 5, we report results from the control function estimator in Wooldridge (2009), and in columns 3 and 6, we report results from the estimator developed by GNR,[13] which estimates the flexible input elasticity in a first stage and subsequently the coefficients on labour and capital.

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 4), we estimate a capital coefficient of 0.19, a labour coefficient of 0.21, and a materials coefficient of

[12] This adjustment can be seen through the lens of partitioned regressions, where the role of capital grants as inputs in the production function is partialled out. With a larger sample, the alternative would be to estimate the production function on data from the control group only. (Note that, when we allow the production function coefficients to differ by treatment – in column 1 of Appendix Table A.3 and column 1 of Appendix Table A.6 – we do not find large or significant differences).

[13] We use Stata code provided by the authors for this.

0.42. We note that, in both columns 1 and 4, the estimated models comfortably pass the relevant specification tests: the Hansen (1982) test of over-identifying restrictions, and the Windmeijer (2018) test of instrument informativeness. The inclusion of lagged output addresses autocorellation in the model as confirmed by the respective Arellano and Bond (1991) test. Using the control function approach in columns 2 and 5, 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. The GNR results in columns 3 and 6 demonstrate small deviations from the previous two models, but not in a particular direction across the two countries.

3.3 Robustness of production function estimates

Before we turn to the TFP analysis, we summarise a comprehensive set of tests of the robustness of our results. This includes (i) utilising all classes of production function estimators used in the literature, to assess consistency across estimators with different underlying assumptions; (ii) testing for internal consistency in production functions across various sub-samples (industry and treatment status); and (iii) assessing the external validity of the results across the two samples and against common results of production functions in the literature, incl. formal firms.

First, we already note that the production function estimates obtained from a control function approach – based on a starkly different set of assumptions – and those from the GNR approach do not differ significantly from those obtained using linear panel methods. Further, in Appendix Tables A.2 and A.5, we report an extensive set of alternative specifications (OLS estimates, fixed effect estimates, dynamic panel estimates with alternative instruments, and Ackerberg et al. (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. To anticipate results in the next section of the paper, neither are our estimated treatment effects of capital grants on productivity sensitive to the way we estimate productivity. The relative consistency between the three main estimator types utilised in the production function literature, which utilise different identifying assumptions, demonstrates the robustness of our results.

Second, turning to internal validity, in Appendix Tables A.3 and A.6, 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.4 and A.7, we show that it is reasonable to pool production functions from different industries – in particular, between traders and non-traders.

Third, considering external validity, we note that the parameters are remarkably similar between Ghana and Sri Lanka.[14] 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 et al., 2020), Colombia (Gandhi et al., 2020) 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 ($\beta_m > \beta_l \geq \beta_k$).

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 main object of interest is the log of total factor productivity (TFP), which we construct as:

$$\log \widehat{TFP}_{it} = y_{it} - \hat{\beta}_k \cdot k_{it} - \hat{\beta}_l \cdot l_{it} - \hat{\beta}_m \cdot m_{it}, \tag{3}$$

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

We estimate the effect of treatment on productivity by exploiting the randomised assignment of treatment:

$$\log \widehat{TFP}_{isct} = \alpha \cdot \log \widehat{TFP}_{i0} + \beta \cdot T_{it} + \gamma_{ct} + \mu_{sc} + \varepsilon_{isct}, \tag{4}$$

pooling microenterprises across all time periods and across both countries, for maximal statistical power. T_{it} is a treatment indicator that turns one after a microenterprise has received a capital grant. The coefficient of interest is β, the productivity treatment effect. For efficiency purposes, and given the large heterogeneity in productivity across firms even at baseline, we estimate an ANCOVA regression which controls for baseline productivity $\widehat{TFP}_{i0}$, following the recommendation by McKenzie (2012). We also include time t and industry s fixed effects separately for each country c (μ_{sc} and γ_{ct}). We calculate in turn TFP using production function coefficients from each of the three methods. For inference, we cluster standard errors at the unit of treatment assignment, which in

[14] 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 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.

this case is the firm (Abadie, Athey, Imbens, and Wooldridge, 2017).

We also implement a fourth approach, which does not try to identify the production function coefficients in a first stage model. Instead, this approach defines productivity in terms of labour productivity $\log(Y/L)$. A potential disadvantage in this context is that, when firms are financially constrained, grants will relax constraints on capital and materials inputs, resulting in a mechanical increase of measured productivity per hour worked. We therefore control for capital and materials inputs directly in the regression (for a recent example of such an approach, see Bloom et al. (2018). We specify – in parallel to equation (4) – an ANCOVA regression model of labour productivity on treatment status that we augment by controls for factor inputs in intensive form (obtained by re-writing production function 2 in terms of $\log(Y/L)$):

$$\log\left(\frac{Y_{it}}{L_{it}}\right) = \alpha \cdot \left(\frac{Y_{i0}}{L_{i0}}\right) + \beta \cdot T_{it} + \tilde{\beta}_k \cdot \log\left(\frac{K_{it}}{L_{it}}\right) + \tilde{\beta}_m \cdot \log\left(\frac{M_{it}}{L_{it}}\right) + \tilde{\beta}_l \cdot \log\left(L_{it}\right) + \gamma_{ct} + \mu_{sc} + v_{isct}. \tag{5}$$

In this model, β identifies the effect of capital grants on labour productivity after controlling for other inputs.

Table 2 presents our main result. Panels A, B and C in turn use as outcome variable TFP estimated using production function coefficients of each the the three approaches of the previous section: a linear panel Blundell and Bond (1998) estimation, a Wooldridge (2009)) control function estimator, and the estimation method proposed by Gandhi et al. (2020). Panel D reports coefficients on treatment and on the input controls from a regression of labour productivity.

Our results are remarkably stable across the four productivity measures. We find that treatment increases productivity significantly by 4-6 percent on average, as well as at the median. We find particularly an outward shift at the top of the distribution: productivity increases by 6-9 percent at the 80th percentile. These effects are statistically significant (although for TFP based on Gandhi et al. (2020) only at upper percentiles, not at the mean or median). We also test for differences in TFP of treated and control microenterprises non-parametrically. We show the distributions in Figure 1. Since the location of the log(TFP) distribution is country-specific, we report separate graphs for Ghana and Sri Lanka, and for each of the three production function estimation methods. Visually, we see that TFP is higher in treated microenterprises than in control firms. The distributions drift apart particularly for higher levels of TFP, consistent with what we found using quantile regressions. We formally test for equality of distributions using a Wilcoxon rank-sum test, and reject equality strongly for Ghana (for each of the three TFP measures) and weakly also for Sri Lanka (for two of the three TFP measures).[15]

[15] We allow for arbitrary correlation within firms across time using randomisation inference, where we simulate re-randomisation using the sampling designs in the original studies.

In sum, these findings suggest the effect of capital grants on profits does not work through the adjustment of homogenous production factors – capital, materials and labour – alone. There is an additional effect of grants on output which is loaded onto measured productivity. This increase in productivity comes from the top of the distribution: capital grants enable the most productive microenterprises to become even more productive.

4.2 Robustness of productivity effects

We assess robustness of our findings in various ways. To begin with, instead of focussing on a single method, we already established a pattern of higher productivity in grant-receiving firms based on four different productivity estimates, each underpinned by sometimes very different sets of assumptions. We find treatment effects not only at the mean, but also at various points of the distribution; this finding is robust to a completely non-parametric test of differences in the entire productivity distributions. All of this should give us confidence that we pick up a common signal about productivity effects of grants across these measurements.

Here, we summarise the results of a number of further robustness exercises (relegating the details in the appendix). First, we use our previous TFP estimates but change the treatment effects estimating equation. Specifically, we omit baseline controls from the estimation, and hence estimate an OLS instead of an ANCOVA treatment effects specification. We obtain very similar results, shown in Table A.8. Second, we consider more alternative TFP measures in Table A.9. Specifically, we construct TFP using, in turn, the production function estimates from Tables A.2 and A.5. These are based on a large array of production function estimators using alternative specifications in addition to those used in Table 2. Again, the magnitude and pattern of our main results are upheld: TFP increases by 4-9 percent at the mean, and by 6-11 percent at the 80th percentile of the TFP distribution.

Third, we explore robustness to different functional forms of the production function. In all our analysis so far, we maintained the assumption of a Cobb-Douglas production function that we made in equation 1. As an alternative, we consider the translog production function, a second degree polynomial expansion in the inputs capital, labour, and materials. This is a flexible empirical approximation to a more general CES production function. As the estimates in Table A.10 show, the results if anything become even stronger under this more flexible functional form. (However, as one would expect, the coefficient estimates for translog in Table A.11 are much noisier than those for Cobb-Douglas.) We further cannot reject the null hypothesis that all second-order terms are jointly zero and hence that the production function is Cobb-Douglas. We therefore conclude that, while our preferred functional form is Cobb-Douglas, our estimates are empirically robust to more flexible functional form assumptions.

Fourth, we explore robustness to alternative measures of the capital stock. In particular, while our main measure of capital stock follows the approach in DMW and FMQW and does not account for asset depreciation, we alternatively allow for a range of plausible depreciation rates for microenterprise capital stock between 5 and 25 percent per year. As Tables A.12 to A.15 show, our results are robust to this entire plausible range of depreciation rates, with minimal quantitative changes. Fifth and finally, we show results that are estimated separately for Sri Lanka and Ghana (Appendix Tables A.16 and A.17). We find very similar patterns in both countries, with TFP increases in the upper part of the distribution.[16]

An alternative interpretation to our findings is that the production function residual reflects higher markups or prices for treated firms, rather than differences in productivity/TFP. While we have no direct information on prices which would allow us to construct physical productivity (TFPQ), we similarly have no information that would allow to make adjustments for product or service quality. Even if price data were available, quality of products or services might also be affected by the treatment – for example, elsewhere in the paper we document upgrading and entry into new markets. For this reason, Atkin et al. (2019) argue that TFPR is a preferable measure of underlying productivity than TFPQ. We separately assess the possibility of higher mark-ups with data on the sales margin of the main product, available in two waves of the Sri Lanka survey.[17] In Appendix Figure A.1, 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 substantial 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 (2019). While this is not the focus of our paper, we nevertheless test for gender heterogeneity in TFP effects in both datasets. Our results (in Tables A.18 and A.19) 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.

Lastly, we consider the difference between productivity effects of different treatment

[16] We note that country-level results are only individually statistically significant in Sri Lanka. However, when we perform a cross-equation test of equality of coefficients across countries – that is, when we run pairwise equality tests of the coefficient on 'Dummy: Treated' between Appendix Tables A.16 and A.17 – we do not reject the null hypothesis that the distributional shifts are the same across countries. (Specifically, the smallest p-value on pairwise comparisons is 0.099, out of 18 separate tests.) Based on this and also the non-parametric evidence which showed a significant improvement in TFP for treated firms in both countries, we conclude that treatment has shifted TFP in both countries in a similar way.

[17] Sales margins are calculated from responses to the question: "Consider the most important item you sell. If you buy Rs. 1000 worth of this product how much revenue will you receive from the sale of this product on average?"

types. In Ghana, we find some evidence that TFP effects are higher for in-kind treatments Appendix Table A.20. These results add a complementary perspective to the 'flypaper effect' discussed by FMQW. The authors find stronger evidence for treatment effects in microenterprises which received in-kind grants (especially those run by women). For Sri Lanka, we cannot reject the null hypothesis that cash and in-kind treatments have the same effect (Appendix Table A.21). The point estimates are somewhat higher for cash treatments.

4.3 How important are the productivity effects of capital grants?

Having established productivity effects of capital grants in a methodologically robust way, we now assess their economic significane. In other words, we turn to the question of much of the effect of capital grants is driven by productivity, and how much is driven by adjustments in production factors. Using the production function in equation 2, we can decompose the average treatment effect (ATE) of capital grants on revenue as follows:

$$\mathbb{E}\left(\frac{\Delta y_{it}}{\Delta z}\right) \approx \mathbb{E}\left(\frac{\Delta a_{it}}{\Delta z}\right) + \beta_k \cdot \mathbb{E}\left(\frac{\Delta k_{it}}{\Delta z}\right) + \beta_l \cdot \mathbb{E}\left(\frac{\Delta l_{it}}{\Delta z}\right) + \beta_m \cdot \mathbb{E}\left(\frac{\Delta m_{it}}{\Delta z}\right), \tag{6}$$

where $a_{it} = \log A_{it}$ is the log of TFP and z is treatment status (which in our case is binary).[18] Equation 6 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 4. 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.[19] We find that changes in TFP account for 6-29% of the treatment effect of capital grants on revenues in Sri Lanka, and 21-40% in Ghana. While estimates from three of the four methods lie close to each other (19-29% in Sri Lanka and 21-35% in Ghana), estimates from the GNR method have higher variance, suggesting variably a very low contribution in Sri Lanka, or a very high contribution in Ghana. The increase in capital stock accounts for about 20% on average, and higher material use contributes on average to around 50%

[18] 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.

[19] 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

of the increase in revenues. The contribution of changes to labour input on revenues is negligible.[20]

4.4 Are effects sustained in the long term?

Improvements in microenterprise productivity are especially noteworthy because they can potentially shift firms into a higher steady-state of capital, revenue and profits (see, for example, the theoretical framework in FMQW), resulting in lasting and not only temporary effects on firm size, revenue, and profits. 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 et al. (2012) report a sustained increase in profits for the treatment group more than six years after the initial capital grants.[21]

In Table 3 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. While increasing firm heterogeneity over time makes the long-run estimates very noisy – as evidenced by the large standard errors – the point estimates are consistent with the idea that TFP *and* fixed capital are sustainably higher in treatment firms, as would have been the predicted effects of a productivity shock in any standard growth model. About six years after the intervention, point estimates for both outcomes are similar to the effects found in the first year (and equality of effects at different time horizons cannot be formally rejected); even though effects are individually not statistically significant beyond two or three years after the intervention, due to increasing noise. The fact that treatment effects on capital do not rise with time suggests that firms treated with grants make all their additional investments right after receiving their grants. Indeed, we find that the asset purchases of treated microenterprises are clustered in the period immediately after the grant payout; there is no crowding-in of follow-up investment (Appendix Figures A.2).

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 a mechanism where productivity effects would be driven by a higher level inventories, for example through reduced stock-outs, better customer choice, or lower re-stocking costs potentially associated with higher invento-

[20] Indeed, it is even slightly negative in Ghana; this is due to a very small but negative treatment effect on labour inputs.

[21] 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.

ries stocks. Rather, these results suggest that the mechanism is related to the purchses of fixed capital assets that grant-receiving firms undertook.

5 Mechanisms

5.1 What kind of capital do capital grants buy?

After documenting the effects of capital grants on productivity as well as the importance of this channel for observed revenue increases, we now examine the mechanisms through which capital grants can enhance productivity. In particular, we test the plausible hypothesis that this occurs through productivity embodied in capital. Solow (1959) originally formalised this idea in an aggregate growth model. Unlike in its better-known cousin – *'the'* Solow (1956) growth model – firm productivity in Solow (1959) does not grow independently of capital investment. Exogenous frontier productivity growth increases availability of newer and more productive capital vintages. But frontier productivity growth does not automatically diffuse to all firms. Instead, technological progress is passed through to a firm only if and when it chooses to replace its old capital stock with the new, more productive frontier variety. Old capital is still perfectly useful (until it randomly breaks down) but newer capital can be used in the same activities more effectively. In other words, firms will lag behind the productivity frontier if they do not possess the most advanced equipment that is available.[22]

To test this mechanism, we turn to the detailed listing of capital assets in the questionnaire from DMW in Sri Lanka.[23] The questionnaire puts individual business into the following categories, as determined in the field by respondents and/or enumerators: business tools or utensils, machinery, furniture and equipment, vehicles, and other physical assets (excluding inventories). Assets were categorised and subsumed under a certain heading in the field by respondents and/or enumerators. We use the categorisation *as it is given in the data* to distinguish between essential businesses assets – such as machinery, tools, and furniture, owned by 90% of firms at baseline – and assets that are less essential. The latter include vehicles and other durable assets, including refrigerators and other household electronics. At baseline, only 30% of firms own any asset in this category.

In addition, since it is not clear which functional categories of capital should embody technology, we additionally hand-code individual items according to whether they have a more advanced technology component, irrespective of which category the items are

[22] The Solow (1959) model is therefore consistent with productivity dispersion among firms, consistent with a large body of modern empirical evidence.

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

recorded in.[24] In our context of Sri Lankan microenterprises, higher-technology assets tend to be powered tools, or items made out of better material than older vintages. These assets generally serve a similar purpose and are useful in similar activities and industries as their less technology-intenstive counterparts. 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.

We find that microenterprises in the treatment group acquire different assets than the control group, and that those assets are technologically more advanced. Table 5 displays the effects of capital grants on different categories of microenterprise capital. As before, we report coefficients on treatment dummy from ANCOVA regressions. We find that, pooled across follow-up waves, microenterprises increase their fixed capital stock by about as much as their inventories stock. 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 only 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. In total, about 70% of the increase in capital comes from high-technology vehicles and durable goods.[25]

This evidence shows 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 essential 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, including vehicles and electronic goods. We show this in Figure 2, which graphs this extensive margin of asset ownership over time for the treatment and control groups. Since at baseline, most firms already own essential assets, this leaves little room for treatment to exert an effect. Indeed, at endline, in both the treatment and the control group, 96% own such item. On the other hand, only 30% of microenterprises own vehicles and durables at baseline. We therefore call these categories 'non-essential' assets. It is in these assets that we see all the effects of treatment. During the intervention window, ownership of non-essential assets climbs to more than 50% for treated firms, but stays unchanged for control firms. While longer-term estimates are again very noisy,

[24] While are aware that this exercise is arguably subjective, we performed this categorisation as one of the first analytical steps in this paper, according to some clear criteria (e.g. is the asset power-operated or not? Is it artisanal or industrially manufactured?). For complete transparency, we provide the complete list of items and our classification in Appendix Table A.25.

[25] In Appendix Table A.23 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.

point estimates suggest that the tilt of the asset composition is sustained over time (Appendix Table A.24).

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 commonly purchased assets in the treatment group are vehicles, refrigerators, and showcases.[26] Refrigerators and showcases make up around 60% of other durable assets, both by quantity and by value. Such items are often not essential for carrying out the small-scale manufacturing, trade and service activities that small Sri Lankan firms engage in. But they can allow business owners to carry out their activities more effectively. Table 7, which reports the effects of treatment on a range of different indicators of how firms do their business, illustrates this. The customer base, the likelihood to introduce new products, and the share of revenue from new products all by about 20% each. We also find statistically significant effects on the share of firms selling refrigerated or perishable products – a tripling and doubling, respectively, relative to the control group – despite the fact that the absolute magnitude of this effect over the entire sample is of course low, and similar to the share of all firms that adopt refrigerators (about 1%). We find no effect on reducing spoilage of goods (Column (6)) or on entry into new businesses or new business locations (Columns (7) or (8)). Taken together, this illustrative evidence suggests that capital grants enabled entrepreneurs to carry out their existing businesses to a higher standard.[27]

An alternative interpretation of our findings on asset ownership is that these changes in the asset composition reflect purchases of consumer durables for use in the entrepreneurs' household consumption, rather than for productive use in the business. If changes in assets were entirely due to private consumption, then we should find no productivity effect accompanying the asset effect. To anticipate results in the next section, we will find that changes in firm productivity are almost entirely driven by changes in the asset composition. Our results illustrating the usefulness of refrigerators for business are also inconsistent with this alternative hypothesis. More generally, if diversion of assets to private consumption is a concern, then our estimates would reflect a lower

[26] These items are much less commonly purchased by the control group. Even though the absolute number of cases for each specific item are small – e.g. fewer than 1% of treated firms purchase refrigerators – the available evidence suggests that increases in these asset categories are substantial. For instance, after receiving capital grants, the number of firms with refrigerators doubles, and the number of bicycles and showcases increases by 50 percent.

[27] Since a large share of firms in our sample are retail firms, the question whether higher 'productivity' does not simply reflect higher prices driven by product quality or price markups. Our finding that sales margins appear to be lower in treated firms (Appendix Figure A.1) suggests that this is not the case. Instead, it seems consistent with the result in Atkin, Faber, and Gonzalez-Navarro (2018) that productivity gains in retail are passed through to lower consumer prices.

bound to the true effects of capital-embodied productivity.[28] To further test this possibility, we test for heterogeneity of results by whether the business is run from home, a proxy for the divertability of business assets. We find no difference in effects (Appendix Table A.26).

5.2 What drives the treatment effect?

To take stock of our findings so far: we have documented that capital grants, viewed through the lens of a standard gross output production function, increase productivity in microenterprises by about 4-6% on average. This explains about 20-30% of the overall effects that capital grants had on revenue, the rest being explained by larger stocks of materials and capital. The expansion of the capital stock in grant-receiving firms is far from uniform: almost all of the extra capital purchases consist of technologically more advanced assets, especially durable goods and vehicles. This suggests that different, more productive capital vintages may be a mechanism behind the effects we document on productivity. But does the effect on productivity work *through* the composition of capital?

To test for whether the increase in productivity can indeed be attributed to the change in the capital composition, we turn to formal mediation analysis. In particular, we estimate the 'average controlled direct effect' (ACDE) proposed by Acharya et al. (2016), which decomposes the effect of treatment T on an outcome (in our case, TFP) into the direct effect of treatment on the outcome while leaving the mediator M constant, and the remainder of the treatment effect which can be attributed to the mediator. Formally, we first estimate the auxiliary model:

$$\log \widehat{TFP}_{isct} = \alpha \cdot \log \widehat{TFP}_{i0} + \beta_1 \cdot T_{it} + \beta_2 \cdot M_{it} + \beta_3 \cdot T_{it} \cdot M_{it} \gamma_{ct} + \mu_{sc} + \epsilon_{isct}, \qquad (7)$$

which augments our baseline TFP effects model with the mean-zero mediator M_{it} and its interaction with treatment status. Second, we de-mediate the outcome by taking out the contribution of the mediator contained to the outcome:

$$\log \widetilde{TFP}_{isct} = \log \widehat{TFP}_{i0} - \hat{\beta}_2 \cdot M_{it} - \hat{\beta}_3 \cdot T_{it} \cdot M_{it}. \qquad (8)$$

The de-mediated outcome is then the outcome that would have ocurred had the level of the mediator been equal to its mean. The third and final step involves estimating the ACDE by repeating the treatment effects regression, but replacing the outcome by its de-mediated value:

$$\log \widetilde{TFP}_{isct} = \alpha \cdot \log \widehat{TFP}_{i0} + \beta_{ACDE} \cdot T_{it} + \gamma_{ct} + \mu_{sc} + \epsilon_{isct}. \qquad (9)$$

[28] One might further hypothesize that assert diversion has an effect on household wealth, or makes them more efficient at home production. This could be reflected in more follow-up investments by wealthier treatment microenterprises, or by an increased labour supply of treated entrepreneurs, as evidence that such mechanisms drive the results. We find no difference in follow-up investments (Appendix Figure A.2) or in hours worked at the firm (Table 4).

We report the results from this exercise in Table 6. We consider four different mediator variables: the logs and the shares of high-tech and non-essential capital. Since these variables are only available in Sri Lanka, we again restrict the analysis to this setting. We find average controlled direct effects that are close to zero and statistically very far from significant. That is, the results imply that essentially the entire effect of treatment of capital grants on measured productivity is explained by the adoption of higher-technology and non-essential assets. Across the three different types of productivity estimates and four mediators considered, we find that between 90% and 130% of the treatment effect is explained by the mediator.

These results lend credence to the interpretation that a mechanism of technology-embodied capital can explain why capital grants incresed microenterprise productivity. We interpret technology here in a broad way, meaning both assets with a higher technology component as well as asset classes (such as non-essential durables and vehicles) that allow the microentrepeneur to run their business more efficiently for a given set of inputs.

6 Conclusion

In this article, we look at microenterprises through the structural lens of a production function. We use several complementary methods to estimate production functions for 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 effects on total factor productivity. A decomposition analysis suggests that returns to capital grants for microenterprises contain a significant return to increased productivity. We find evidence for a plausible mechanism behind this: capital items that embody superior technology allow firms to improve total factor productivity. Treated firms acquire more technologically-advanced asset vintages, and invest into capital that previously played a less essential role for firms, such as vehicles and durables. Firms change how they do business as a consequence: we find that they serve more customers, introduce and sell more new products. We also find suggestive evidence of lower prices for consumers.

Taken as a whole, our results provide a more nuanced interpretation to the previous assumption in this literature that treatment effects reflect returns to capital alone. This has three main implications for our understanding of microenterprises – and, more generally, for the design of policy that provides capital to such firms (whether through grants or through microfinance).

First, our results have implications for the scale of potential transfers. If we believe that the impact of capital grants operates exclusively through a capital channel, we should anticipate that the highest marginal returns should accrue to small grants (given diminishing returns to capital in any standard production function framework); in turn, this implies that optimal policy for the distribution of capital should be to provide a large number of small grants or small loans. In contrast, the productivity effect that we find in this paper, both in our main results and in our results on higher-technology durables, imply that capital returns are likely to be non-convex – in the sense that they require a relatively large and lumpy change in the capital stock, of the kind observed in both the Sri Lankan and Ghanaian studies. This implies that policies on capital provision – again, whether through cash grants or through microfinance – should be sufficiently large as to encourage a shift in the kind of capital that a microenterprise is using. Put differently, the kind of capital upgrading that we document in this paper is clearly a non-marginal behaviour. This is consistent with recent evidence from the microfinance literature, suggesting that larger transfers – and, in particular, asset-based transfers – may provide for important gains that smaller transfers do not (see, in particular, Bauchet and Morduch (2013), Bari, Malik, Meki, and Quinn (2021) and Bryan, Karlan, and Osman (2021)).

Second, if we believe that capital grants operate exclusively through a capital channel, we should anticipate the impact of capital grants to be transitory (as in the model, for example, in Fafchamps et al. (2014)). In contrast, the result that lumpy transfers have TFP effects implies that the impact of such transfers is likely to be highly persistent. This is consistent with our results (as discussed in section 4.4), and with evidence showing long-term impacts of the Sri Lankan capital drops (de Mel et al., 2012). This has direct relevance for policy design; any welfare assessment of the value of capital transfers needs to make some assumption about the time horizon over which the gains are likely to be enjoyed.

Third, and most generally, we see our results as speaking to broader policy debates on the persistence of small informal firms in developing economies (Hsieh and Klenow, 2009; Meghir, Narita, and Robin, 2015; Ulyssea, 2018). Such debates often view microenterprises as having intrinsically low productivity – and, therefore, such debates are often very pessimistic about the prospects for encouraging growth through sustainable microenterprise expansion. Our results suggest cause for guarded optimism in this space; by showing that capital transfers can enable firms to adopt higher-technology durables, and that such durable adoption explains TFP increases, we show that there are prospects for technological upgrading, and that such upgrading can be facilitated through capital transfers.

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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) Gandhi-Navarro-Rivers	(4) Blundell-Bond	(5) Wooldridge	(6) Gandhi-Navarro-Rivers
Log capital	0.18**	0.16***	0.25***	0.19***	0.08***	0.17***
	(0.07)	(0.02)	(0.03)	(0.07)	(0.02)	(0.04)
Log labour	0.13***	0.20***	0.17***	0.21***	0.19***	0.22***
	(0.05)	(0.03)	(0.03)	(0.05)	(0.03)	(0.06)
Log materials	0.41***	0.45***	0.54***	0.42***	0.55***	0.32***
	(0.06)	(0.03)	(0.01)	(0.09)	(0.02)	(0.01)
L.Log revenue	0.37***			0.22***		
	(0.06)		(0.04)			
Observations	2610	2499	2289	3105	2313	2071
Microenterprises	382	379	372	770	724	696
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		

Note: Estimators employed are Blundell and Bond (1998) System GMM, the Wooldridge (2009) control function estimator, and the Gandhi et al. (2020) estimator. All models partial out for wave dummies and post-treatment status (not reported). For the GMM estimators 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. Capital stock and profits are measured in real national currency. Profits are measured monthly and hours worked are measured weekly. Standard errors are clustered at the microenterprise level. For GNR, standard errors are obtained from a bootstrap with 2000 replications, like in Gandhi et al. (2020). *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

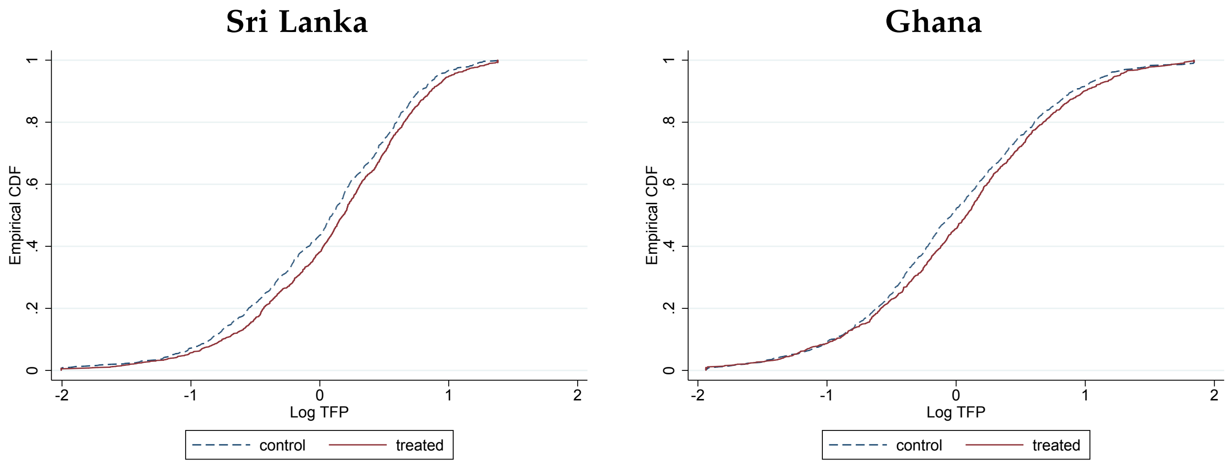
Table 2: **Capital grant treatment effects across all measures of productivity (Sri Lanka and Ghana - pooled)**

	(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(TFP) estimated using Gandhi-Navarro-Rivers estimator						
Dummy: Treated	0.04	-0.01	0.03	0.04	0.05*	0.06*
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	4777	4777	4777	4777	4777	4777
Microenterprises	1114	1114	1114	1114	1114	1114
D. 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

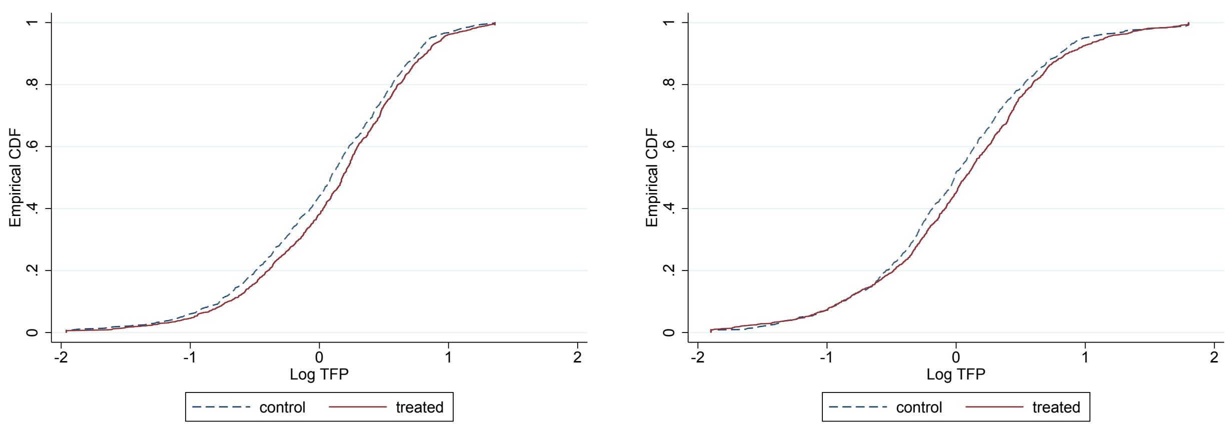
Note: This table reports the effect of treatment on TFP at different moments of the distribution, for microenterprises in Ghana and Sri Lanka. In Panel A, TFP is estimated using the Blundell and Bond (1998) System GMM estimator. In Panel B, TFP is estimated using the Wooldridge (2009) control function estimator. In Panel C, TFP is estimated using the Gandhi et al. (2020) estimator. In panel D, 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.

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

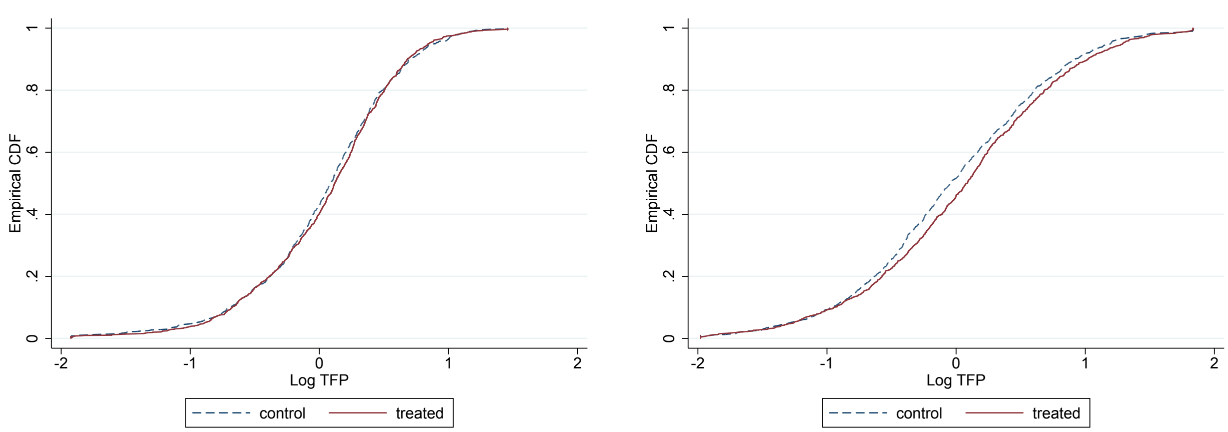
(a) Blundell-Bond



(b) Wooldridge



(c) Gandhi-Navarro-Rivers



Note: CDFs of TFP for treated and untreated microenterprises in the post-treatmenet waves. Wilcoxon rank-sum test of equality of distribution p-values: 0.085 (Sri Lanka, Blundell-Bond), 0.094 (Sri-Lanka, Wooldridge), 0.360 (Sri Lanka, GNR) and 0.001 (Ghana, Blundell-Bond), 0.001 (Ghana, Wooldridge), 0.007 (Ghana, GNR). P-values were obtained using randomisation inference (with 200,000 replications) and take into account the clustering of the data at the level of the microenterprise across survey waves.

Table 3: **Long-term effects of capital grants on productivity, capital, and intermediate inputs (Sri Lanka)**

	(1) ln(TFP)	(2) Fixed capital	(3) Inventories	(4) Total expenditure
Dummy: Treated × Year 1	0.09*	4006.32***	5061.97***	4340.33**
	(0.05)	(997.69)	(1552.18)	(1953.94)
Dummy: Treated × Year 2	0.11**	3429.04**	2671.51	3272.91
	(0.06)	(1365.87)	(1855.43)	(2604.60)
Dummy: Treated × Year 3	0.05	3480.80*	643.78	3431.19
	(0.07)	(1865.63)	(2129.55)	(3420.30)
Dummy: Treated × Years 5-6	0.08	4603.97	827.50	1424.98
	(0.07)	(4131.12)	(2260.96)	(1947.52)
Control mean: baseline	-0	12,624	14,131	8,832
Control mean: 3 years	0	22,647	14,606	27,785
Observations	4,164	4,763	4,749	4,650
Microenterprises	385	385	385	385
p-value: Year 1 = Year 2	0.53	0.44	0.06	0.45
p-value: Year 1 = Year 3	0.52	0.73	0.01	0.72
p-value: Year 1 = Year 4	0.92	0.88	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. Fixed capital is the total fixed capital stock excluding land and buildings, as defined in the main text. Inventories is the stock of inventories, raw and finished unsold materials. Total expenditure is total business expenditure in the last month, minus the wage bill. All regressions are ANCOVA and control for wave dummies. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table 4: **Decomposing the effect of capital grants on revenue**

Sample:	**Sri Lanka**				**Ghana**			
Production function estimates:	Blundell-Bond	Wooldridge	GNR	OLS (Y/L)	Blundell-Bond	Wooldridge	GNR	OLS (Y/L)
Treatment effect: Revenue	0.202	0.202	0.202	0.202	0.140	0.140	0.140	0.140
Treatment effect: TFP	0.059	0.054	0.011	0.038	0.049	0.048	0.056	0.030
Treatment effect: Capital	0.307	0.307	0.307	0.307	0.173	0.173	0.173	0.173
Treatment effect: Materials	0.190	0.190	0.190	0.190	0.140	0.140	0.140	0.140
Treatment effect: Labour	0.050	0.050	0.050	0.050	-0.007	-0.007	-0.007	-0.007
Contribution: TFP	0.290	0.268	0.055	0.190	0.352	0.346	0.402	0.212
Contribution: Capital	0.280	0.247	0.375	0.168	0.234	0.103	0.213	0.131
Contribution: Materials	0.381	0.420	0.507	0.593	0.416	0.553	0.389	0.622
Contribution: Labour	0.033	0.049	0.043	0.056	-0.011	-0.010	-0.009	-0.010

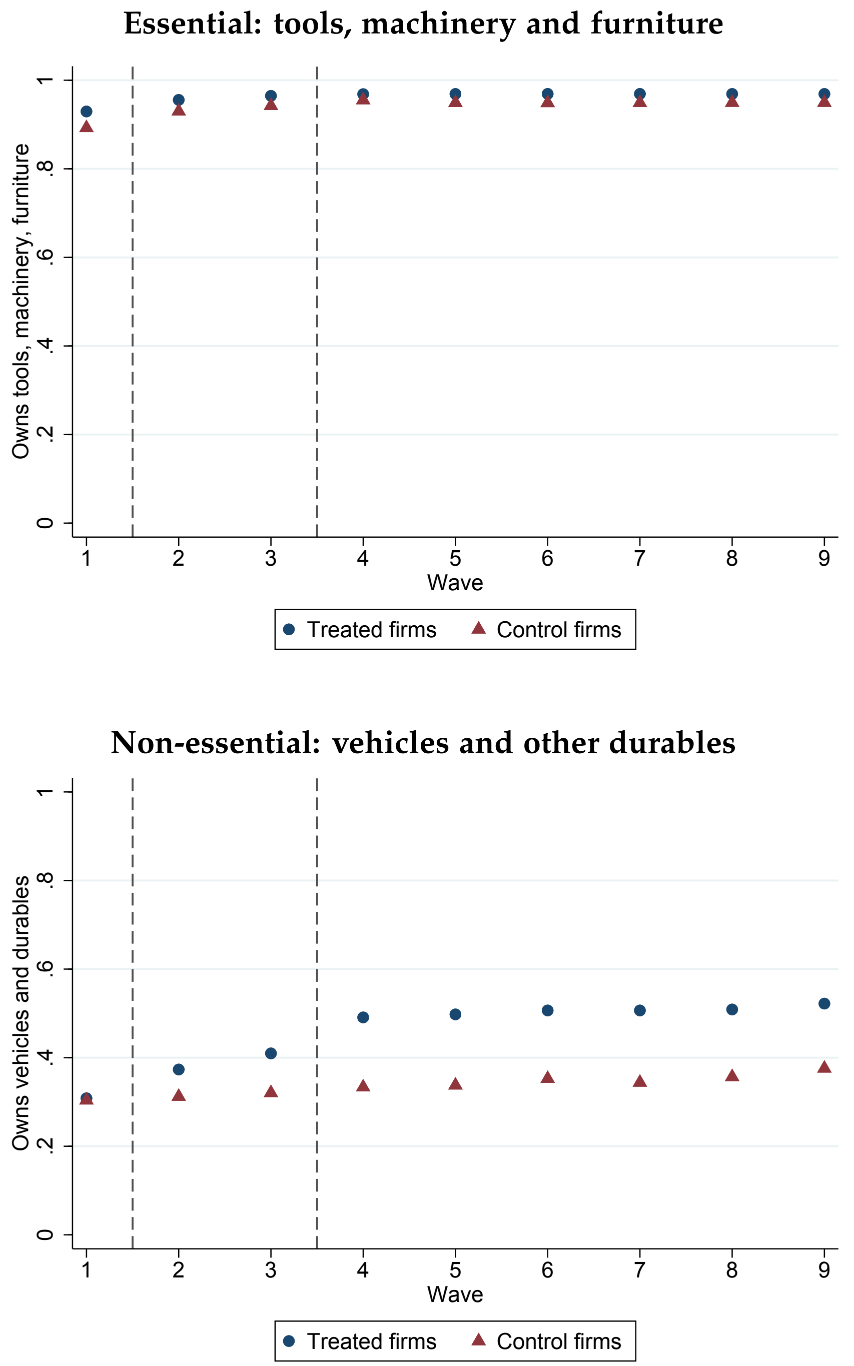
Note: This table decomposes the effect of capital grants on revenue into the contribution of TFP and the contribution of production factors, following equation 6. Average treatment effects (ATE) are estimated with OLS. Relative contributions of each factor are calculated according to equation (6) by 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.

Table 5: **Effects of capital grants on microenterprise capital (Sri Lanka)**

	(1) Inventories	(2) Fixed capital	(3) Machines, tools & furniture	(4) Vehicles & other durables	(5) Low-tech capital	(6) High-tech capital
Dummy: Treated	3904.62**	3594.79***	688.70	2630.88***	697.04**	2814.05***
	(1608.33)	(961.61)	(712.43)	(625.69)	(320.58)	(892.88)
Control mean	14,015	15,555	11,581	3,763	4,717	10,838
Observations	3,358	3,341	3,329	3,345	3,341	3,341
Microenterprises	385	385	385	385	385	385

Note: This table breaks down the effect on grants on different categories of capital. 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. All specifications control for wave dummies and baseline values of the dependent variable. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Figure 2: **Ownership of fixed assets: Treatment and control by wave (Sri Lanka)**



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.

Table 6: **Mediation analysis using average controlled direct effects (ACDE)**

Mediator:	(1)	(2) Log Tech Capital	(3) Log Non-Essential Capital	(4) Share Tech Capital	(5) Share Non-Essential Capital
A. Dependent variable: log(TFP) estimated using Blundell-Bond estimator					
Average Treatment Effect (ATE)	0.08*				
	(0.045)				
Average Controlled Direct Effect (ACDE)		0.00	0.01	-0.00	-0.00
		(0.045)	(0.045)	(0.045)	(0.045)
Observations	3036	3032	3036	3032	3036
Explained by mediator (%)		94.9	86.1	104.8	103.9
B. Dependent variable: log(TFP) estimated using Wooldridge estimator					
Average Treatment Effect (ATE)	0.07*				
	(0.042)				
Average Controlled Direct Effect (ACDE)		0.00	0.01	-0.00	-0.00
		(0.042)	(0.042)	(0.042)	(0.042)
Observations	3036	3032	3036	3032	3036
Explained by mediator (%)		94.6	86.9	104.1	104.3
C. Dependent variable: log(TFP) estimated using Gandhi-Navarro-Rivers estimator					
Average Treatment Effect (ATE)	0.02				
	(0.036)				
Average Controlled Direct Effect (ACDE)		-0.01	-0.00	-0.00	-0.01
		(0.036)	(0.036)	(0.036)	(0.036)
Observations	3036	3032	3036	3032	3036
Explained by mediator (%)		126.5	114.6	119.0	128.0

Note: This table uses the method of **?** to calculate the Average Controlled Direct Effect (ACDE) for TFP, using as mediators the level (in logarithms) and share of high-tech and non-essential capital, respectively.

Table 7: **Effects of capital grants on business practices, market and product scope (Sri Lanka)**

	(1) Customers	(2) New product introduction	(3) New product sales	(4) Refrigerated product	(5) Perishable product	(6) Materials spoilage	(7) New business	(8) New location
Dummy: Treated	2.095**	0.010	0.382**	0.007*	0.011*	0.001	0.001	-0.001
	(1.054)	(0.011)	(0.187)	(0.004)	(0.006)	(0.002)	(0.005)	(0.004)
Control mean	11.831	0.049	1.492	0.003	0.011	0.009	0.013	0.007
Observations	3267	2233	2890	2233	2233	3244	3358	2961
Microenterprises	385	385	385	385	385	385	385	385

Note: This table reports the effect of treatment on business practices. The first column is estimated using ANCOVA, columns (2) to (8) are estimated using OLS. New product introduction and share of sales from new product refer to past three months. Perishable and refrigerated products are coded from the names of new products introduced. Materials spoilage is the share of all materials purchased in the past month that were spoiled in the past month. New business and new location refers to business respondent was running in the previous survey round, three months ago. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Online Appendix

A Data construction

We use the public data sets and replication files available from the author's web sites. Wherever possible, we use variables as cleaned and processed by DMW and FMQW. We refer the reader to de Mel et al. (2008) and Fafchamps et al. (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 during the reference month – the last month before the survey – across all respective activities of a business: manufacturing, trade, and services. The precise questions are in Sri Lanka: "What was the total sales last month of products your business makes or alters?", "What was the total sales last month of products your business did not make?" and "What was the total business revenue last month from selling services?" and in Ghana: "What were the total monthly sales of your business? Include sales of 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[29] estimated using the Blundell and Bond (1998) "system GMM" estimator, as well as with the Wooldridge (2009) GMM implementation of 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

[29] 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 et al., 2020); however, we do not view that as a reasonable restriction for this context.

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.2 to A.7, 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 et al. (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.[30]

Control function estimators further require the researcher to make precise economic assumptions about the timing of input choices. Ackerberg et al. (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:

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

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

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

and the instruments are given by:

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

[30] 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.

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 et al. (2015) in column (8) of Tables A.2 and A.5.

B.3 Gandhi, Navarro and Rivers estimator

The production function approach suggested by GNR responds to the concern that flexible inputs (materials, electricity, etc.) are not adequately identified in the above structural estimators, because the invertibility assumption may not hold. This means that flexible inputs cannot be used to proxy for unobserved productivity. To solve this, GNR develop an empirical strategy that, relying on the first order conditions of the firm, nonparametrically identifies the flexible input elasticity. This solves for the missing source of identification for the production function within a proxy variable structure. Within the context of informal firms, one might, on conceptual grounds, expect measurement error and financial constraints to pose a challenge to invertibility.

We implement the GNR approach using code shared by the authors. We utilise this specification exactly without custom changes, so the methodology remains consistent with that of the authors. The estimator follows a two-step approach. The first stage estimates a nonparametric regression of the flexible input's revenue share on all inputs (labor, capital, and intermediate inputs) and identifies the flexible input elasticity. The second stage then uses dynamic panel/proxy variable conditional moment restrictions based on lagged input decisions for the remaining inputs. In this way, the gross output production function and productivity can be non-parametrically identified. We utilise the Cobb-Douglas specification of the production function, consistent with our other estimates.

Once we have established the parameters of the production function, we manually calculate the TFP residual using the estimated coefficients on inputs, consistent with our approach across all estimators.

Online Appendix Tables and Figures

Table A.1: **Test for differential non-response and attrition**

	(1)	(2)	(3)	(4)	(5)	(6)
	Missing data on ...					Attrition
	Capital	Labour	Materials	Output	Any	
			A. Sri Lanka			
ln(TFP)	0.01*	-0.01	0.00	-0.00	-0.01	-0.00
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)
Dummy: Treated	-0.00	-0.01	-0.01	-0.01	-0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
ln(TFP) $\times$ **treated**	-0.02**	0.00	-0.00	-0.01	-0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)
Control mean	0.057	0.059	0.023	0.027	0.101	0.005
Observations	2,688	2,688	2,688	2,688	2,688	2,374
Microenterprises	385	385	385	385	385	385
			B. Ghana			
ln(TFP)	-0.00	-0.00	0.01	0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Dummy: Treated	0.00	-0.01	-0.02	-0.00	-0.02*	-0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln(TFP) $\times$ **treated**	0.02**	-0.00	-0.01	-0.01	-0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Control mean	0.068	0.112	0.091	0.081	0.158	0.040
Observations	2,485	2,485	2,485	2,485	2,485	1,878
Microenterprises	742	742	742	742	742	729
Observations	2,485	2,485	2,485	2,485	2,485	1,878
Microenterprises	742	742	742	742	742	729
Control mean	0.068	0.112	0.091	0.081	0.158	0.040

Note: This table tests for patterns of missing TFP data and survey attrition by treatment status and TFP, as well as its interaction. Time-varying treatment status and TFP refer to the period immediately before the firm attrited or failed to respond. Each regression controls for wave dummies. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table A.2: **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 Ackerberg et al. (2015) estimator. 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.3: **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.4: **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.5: **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 Ackerberg et al. (2015) estimator. 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.6: **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.7: **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.8: **TFP effects: no baseline controls (Sri Lanka and Ghana - pooled)**

	(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
B. Dependent variable: log(TFP) estimated using Gandhi-Navarro-Rivers estimator						
Dummy: Treated	0.04	-0.01	0.03	0.04	0.05*	0.06*
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	4777	4777	4777	4777	4777	4777
Microenterprises	1114	1114	1114	1114	1114	1114
D. 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) control function estimator. In Panel C, TFP is estimated using the Gandhi et al. (2020) estimator. In panel D, the dependent variable is the standard measure of labor productivity. All regressions include wave-times-survey and industry-times-country fixed effects.

Table A.9: **TFP Effects: Alternative production function estimators (Sri Lanka and Ghana - pooled)**

TFP estimation method:	(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
Regression: ANCOVA (mean)	0.04	0.09***	0.07**	0.08**	0.06**	0.04	0.07**	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Regression: Quantile (0.2)	-0.00	0.05	0.04	0.04	0.02	0.02	0.03	-0.00
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Regression: Quantile (0.4)	0.03	0.07*	0.05	0.06	0.04	0.03	0.05	0.04
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)
Regression: Quantile (0.5)	0.05	0.10**	0.08**	0.09**	0.07**	0.02	0.07**	0.06**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)
Regression: Quantile (0.6)	0.06**	0.11***	0.10***	0.10***	0.10***	0.05	0.10***	0.07***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Regression: Quantile (0.8)	0.07**	0.11***	0.10**	0.10**	0.10***	0.06*	0.10***	0.06**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)

Note: This table reports robustness of the TFP effects of capital grants to additional alternative production function estimators. Each column corresponds to a different TFP measure, constructed using the corresponding production function estimates from Table A.2 for Sri Lanka and A.5 for Ghana. Each row corresponds to a different outcome variable in the regression, corresponding to the models in Table 2. As before, 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: Alternative functional form of production function (translog) (Sri Lanka and Ghana - pooled)**

	(1) ANCOVA	(2) Quantile (0.2)	(3) Quantile (0.4)	(4) Quantile (0.5)	(5) Quantile (0.6)	(6) Quantile (0.8)
Dummy: Treated	0.06**	-0.00	0.04	0.08**	0.09***	0.10***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	4777	4777	4777	4777	4777	4777
Microenterprises	1114	1114	1114	1114	1114	1114

Note: This table reports the robustness to functional form of the effect of treatment on TFP at different moments of the distribution, for microenterprises in Ghana and Sri Lanka. TFP is estimated using a translog functional form:

$$y_{it} = \beta_1 \cdot k_{it} + \beta_2 \cdot l_{it} + \beta_3 \cdot m_{it} + \beta_4 \cdot k_{it}^2 + \beta_5 \cdot l_{it}^2 + \beta_6 \cdot m_{it}^2 + \beta_7 \cdot k_{it} \cdot l_{it} + \beta_8 \cdot l_{it} m_{it} + \beta_9 \cdot m_{it} \cdot k_{it} + v_{it}$$

and via OLS. Regressions include wave-times-survey fixed effects, and control for baseline TFP.

Table A.11: **Production Function: Alternative functional form of production function (translog)**

	Sri Lanka		Ghana	
	(1)	(2)	(3)	(4)
Specification:	Blundell-Bond: CD	Blundell-Bond: Translog	Blundell-Bond: CD	Blundell-Bond: Translog
Log capital	0.18**	0.44	0.19***	-0.28
	(0.07)	(0.43)	(0.07)	(0.50)
Log labour	0.13***	0.02	0.21***	-0.57
	(0.05)	(0.80)	(0.05)	(1.10)
Log materials	0.41***	0.60**	0.42***	0.77*
	(0.06)	(0.25)	(0.09)	(0.44)
L.Log revenue	0.37***	0.28***	0.22***	0.17***
	(0.06)	(0.05)	(0.04)	(0.04)
Capital squared		0.01		0.00
		(0.03)		(0.04)
Materials squared		0.05***		0.04
		(0.01)		(0.03)
Labour squared		0.05		0.04
		(0.07)		(0.16)
Log capital * Log materials		-0.07*		-0.05
		(0.03)		(0.06)
Log capital * Log labour		0.01		0.13
		(0.06)		(0.11)
Log labour * Log materials		-0.06		-0.07
		(0.05)		(0.10)
Observations	2610	2610	3105	3105
Microenterprises	382	382	770	770
Hansen (p-value)	0.10	0.24	0.45	0.15
$\hat{\beta}_k + \hat{\beta}_l + \hat{\beta}_m$	0.72	1.06	0.81	-0.08
Constant returns (p)	0.00		0.04	
AR(1) (p)	0.00	0.00	0.00	0.00
AR(2) (p)	0.52	0.16	0.24	0.28
Translog Terms (p)		0.99		0.42
Instruments	77.00	197.00	45.00	102.00
Underidentification (p-values):				
Log capital	0.01	0.01	0.00	0.00
Log labour	0.00	0.00	0.00	0.00
Log materials	0.00	0.00	0.00	0.00
L.Log revenue	0.01	0.01	0.00	0.00
L.Log capital				
L.Log labour				
L.Log materials				

Note: Estimators employed are a Cobb-Douglas and Translog version of Blundell and Bond (1998) System GMM. 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, a test of the joint significance of additional translog terms, 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 A.12: **TFP effects: Assumed depreciation 10% per year (Sri Lanka and Ghana - pooled)**

	(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	0.06*	0.04	0.03	0.06*	0.08*	0.08**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	4830	4830	4830	4830	4830	4830
Microenterprises	1111	1111	1111	1111	1111	1111
B. Dependent variable: log(TFP) estimated using Wooldridge estimator						
Dummy: Treated	0.06**	0.02	0.05	0.07**	0.09***	0.08**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
Observations	4830	4830	4830	4830	4830	4830
Microenterprises	1111	1111	1111	1111	1111	1111
C. Dependent variable: log(revenue/hours worked)						
Dummy: Treated	0.05*	0.02	0.03	0.05*	0.05**	0.07**
	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.03)
Log(Capital/labour)	0.07***	0.02	0.03***	0.04***	0.04***	0.07***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Log(Materials/labour)	0.59***	0.74***	0.73***	0.71***	0.68***	0.58***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Log labour	-0.09***	-0.06*	-0.05**	-0.06**	-0.07***	-0.11***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	4830	4830	4830	4830	4830	4830
Microenterprises	1111	1111	1111	1111	1111	1111

Note: This table reports the effect of treatment on TFP assuming that capital depreciates at 10% per year, instead of at 0% as in the baseline data. The regression pools 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) control function estimator. 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. Results assuming 5% depreciation are identical at the reported level of rounding.

Table A.13: **TFP effects: Assumed depreciation 15% per year (Sri Lanka and Ghana - pooled)**

	(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	0.06*	0.04	0.03	0.06	0.08*	0.08**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	4830	4830	4830	4830	4830	4830
Microenterprises	1111	1111	1111	1111	1111	1111
B. Dependent variable: log(TFP) estimated using Wooldridge estimator						
Dummy: Treated	0.07**	0.02	0.05	0.07**	0.09***	0.08**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
Observations	4830	4830	4830	4830	4830	4830
Microenterprises	1111	1111	1111	1111	1111	1111
C. Dependent variable: log(revenue/hours worked)						
Dummy: Treated	0.05*	0.02	0.04	0.05*	0.05**	0.07**
	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.03)
Log(Capital/labour)	0.07***	0.02	0.03***	0.04***	0.04***	0.07***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Log(Materials/labour)	0.59***	0.74***	0.73***	0.71***	0.68***	0.58***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Log labour	-0.09***	-0.06**	-0.05**	-0.06**	-0.07***	-0.11***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	4830	4830	4830	4830	4830	4830
Microenterprises	1111	1111	1111	1111	1111	1111

Note: This table reports the effect of treatment on TFP assuming that capital depreciates at 15% per year, instead of at 0% as in the baseline data. The regression pools 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) control function estimator. 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.14: **TFP effects: Assumed depreciation 20% per year (Sri Lanka and Ghana - pooled)**

	(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	0.06*	0.04	0.03	0.06	0.07*	0.08**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	4827	4827	4827	4827	4827	4827
Microenterprises	1111	1111	1111	1111	1111	1111
B. Dependent variable: log(TFP) estimated using Wooldridge estimator						
Dummy: Treated	0.07**	0.03	0.04	0.07**	0.09**	0.08**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	4827	4827	4827	4827	4827	4827
Microenterprises	1111	1111	1111	1111	1111	1111
C. Dependent variable: log(revenue/hours worked)						
Dummy: Treated	0.05*	0.02	0.04	0.05*	0.05**	0.07**
	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.03)
Log(Capital/labour)	0.07***	0.02	0.03***	0.04***	0.04***	0.07***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Log(Materials/labour)	0.59***	0.74***	0.73***	0.71***	0.68***	0.58***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Log labour	-0.09***	-0.06*	-0.05**	-0.06**	-0.07***	-0.11***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	4827	4827	4827	4827	4827	4827
Microenterprises	1111	1111	1111	1111	1111	1111

Note: This table reports the effect of treatment on TFP assuming that capital depreciates at 20% per year, instead of at 0% as in the baseline data. The regression pools 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) control function estimator. 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.15: **TFP effects: Assumed depreciation 25% per year (Sri Lanka and Ghana - pooled)**

	(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	0.06*	0.03	0.03	0.06	0.08*	0.08**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	4827	4827	4827	4827	4827	4827
Microenterprises	1111	1111	1111	1111	1111	1111
B. Dependent variable: log(TFP) estimated using Wooldridge estimator						
Dummy: Treated	0.07**	0.03	0.05	0.07**	0.09**	0.08**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	4827	4827	4827	4827	4827	4827
Microenterprises	1111	1111	1111	1111	1111	1111
C. Dependent variable: log(revenue/hours worked)						
Dummy: Treated	0.05*	0.02	0.03	0.05*	0.05**	0.07**
	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.03)
Log(Capital/labour)	0.07***	0.02	0.03***	0.04***	0.04***	0.07***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Log(Materials/labour)	0.59***	0.74***	0.73***	0.71***	0.68***	0.58***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Log labour	-0.09***	-0.06*	-0.05**	-0.06***	-0.07***	-0.11***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	4827	4827	4827	4827	4827	4827
Microenterprises	1111	1111	1111	1111	1111	1111

Note: This table reports the effect of treatment on TFP assuming that capital depreciates at 25% per year, instead of at 0% as in the baseline data. The regression pools 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) control function estimator. 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.16: **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) control function estimator. 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.17: **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) control function estimator. 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.18: **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) control function estimator. 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.19: **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) control function estimator. 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.20: **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) control function estimator. 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.21: **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) control function estimator. 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.22: **TFP effects: Lee (2009) Bounds on non-response and attrition (Sri Lanka and Ghana - pooled)**

	Bounds: Missing data		Bounds: Missing + Attrition	
	Lower	Upper	Lower	Upper
A. Raw productivity differences				
Blundell-Bond log(TFP)	0.04*	0.11***	0.04*	0.11***
	(0.03)	(0.03)	(0.03)	(0.03)
Wooldridge log(TFP)	0.04	0.11***	0.04	0.11***
	(0.02)	(0.03)	(0.02)	(0.03)
log(revenue/hours worked)	0.51***	0.68***	0.51***	0.68***
	(0.07)	(0.07)	(0.07)	(0.07)
Non-missing observations	4,777	4,777	4,777	4,777
Total observations	5,673	5,673	5,708	5,708
B. Productivity with controls from Table 2 partialled out				
log(TFP) estimated using Blundell-Bond	0.02	0.09***	0.02	0.09***
	(0.02)	(0.02)	(0.02)	(0.03)
log(TFP) estimated using Wooldridge	0.02	0.09***	0.02	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)
log(revenue/hours worked)	0.01	0.08***	0.01	0.08***
	(0.02)	(0.02)	(0.02)	(0.02)
Non-missing observations	4,777	4,777	4,777	4,777
Total observations	5,673	5,673	5,708	5,708

Note: This estimates Lee (2009) bounds for the treatment effect on TFP. Panel A bounds raw TFP differences between treatment and control groups in the post-treatment periods used previously for analysis. Panel B bounds residual TFP differences, with control variables as specified in Table 2 partialled out. The large differences for log(revenue/hours worked) are explained by the fact that Panel B controls for other production factors (capital and materials intensity of production) whereas Panel A does not. *, ** and *** denote significance at the 10, 5 and 1 per cent levels.

Table A.23: **Effects of grants on capital: intensive and extensive margin by category (Sri Lanka)**

	(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.

Table A.24: **Long-term effects of grants on different categories of capital: (Sri Lanka)**

	(1) Machines, tools & furniture	(2) Vehicles & other durables	(3) Low-tech capital	(4) High-tech capital
Dummy: Treated × Year 1	1211.88*	2681.68***	576.17*	3357.29***
	(654.18)	(658.34)	(326.40)	(898.31)
Dummy: Treated × Year 2	914.64	2510.42***	702.30	2648.49**
	(1007.41)	(755.05)	(447.40)	(1205.17)
Dummy: Treated × Year 3	900.29	2345.26**	976.40	2435.44
	(1402.32)	(924.58)	(700.92)	(1542.89)
Control mean: baseline	9,257	3,262	3,941	8,683
Control mean: 3 years	15,070	6,963	7,424	15,224
Observations	4,749	4,767	4,197	4,197
Microenterprises	385	385	385	385
p-value: Year 1 = Year 2	0.62	0.64	0.56	0.30
p-value: Year 1 = Year 3	0.78	0.64	0.47	0.46

Note: This table shows the evolution of effects of capital grants on different categories of capital. Breakdown of individual asset items, needed to categorise assets, is 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 A.25: **Categorisation of individual asset items**

Low technology	Higher technology component

Note: The column-wise categorisation of asset items into 'low technology' and 'higher technology' component was done by the authors. The categorisation of asset items into different functional categories (the row-blocks, e.g. 'Tools', 'Machinery', 'Other durables') corresponds to different sections on the survey questionnaire asset module and was undertaken by enumerators and/or respondents in the field. We take that latter categorisation at face value and assume it corresponds to a distinction by functional categories of items.

Low technology	Higher technology component
Tools	
Water Production related items	Industrial equipment
Carpentry tools	Electronic Scales
Fabric painting tools	Welding equipment
Cosmetics	Steamer
Cake making tools	Air Pump
Types of Keys	Computer
Staves	Bower fan
Tool set	Iron
Scale Weights	Hydrometer
String hop	Battery Charger
Fisheries related products	Battery Testers
Motor spare parts	Multi meter
Tires & Tubes	Iron
Basin	Curtain cutting machine
Plastic Items	Calculator
Household equipment	Coir industry related machinery
Bucket	Gold Furnance
Firestone	Rippon meter
Bottle	Video camera
Hanger	Highvoltage meter
Brass	
Iron rod	
Other business equipment	
Aluminum equipment	
Bicycle spare parts	
Bacale rim rapire tools	
Pencil, Glue & Rulers	
Sewing equipment	
Leather Products	
Toddy Production equpment	

Table A.25: **Categorisation of individual asset items**

Low technology	**Higher technology component**
Service Diagram	
Tools required for packing	
Materials required for fishing	
Buildings related tools	
Spare parts required for telephone repairs	
Drink crate	
Oil containers	
Musical Equipment	
Sports Equipment	
Blackboard	
Coil waring tools	
Equipment used to manufacture books	
Toys	
Machinery	
Spoke cutter	Router Machine
String hopper mould	Sander
Spanner	Drill
Rubber wheel	Welding drill
Hand drill	Compressor
Watch repair kits	IC Paint Machine
Polish sealer	Heater
Hitskit	Season machine
Bacal rim tools	Water pump
Curtain for machine	Building block machine
Nescafe filter	Oxygen Plant
	Air conditioner
	Sawing machine
	Carpentry machine
	Air machine
	Hair cutter
	Hair dryer
	Gickshaw
	Hair Iron
	Machine motor
	Key cutting machine
	Button hole machine
	Aluminum cutting machine
	Timber lathe machine
	Scanner machine
	Polisher cutting machine

Table A.25: **Categorisation of individual asset items**

Low technology	Higher technology component
	Vulcanizing
	Washing machine
	Letter cover machine
	Coir spinning wheel
	Spray gun
	Steel cutter
	Bottling machine
	Labeling machine
	Grinder
	Pop rivet gun
	Toaster
	Vehicle Service machine
	Tire removing machine
	Display checker
	Gem cutting machine
	Coir spinner
	Paper cutting machine
	Glass cutter
	Cashew peeler
	Gold Pressing machine
	Digital printer
	Cain Cleaner
	Batik printer
	Electric Cutter (Clothes)
	The machine for shapes the eyebrows
Furniture	
Table	
Shelves	
Cupboard	
Types of chairs	
Wooden Boxes	
Frames	
Wooden Door	
Plywood	
Picces of wood	
Wooden Cabinets	
Dressing table	
Vehicles	
Bicycle	Catamaran/Boat

Table A.25: **Categorisation of individual asset items**

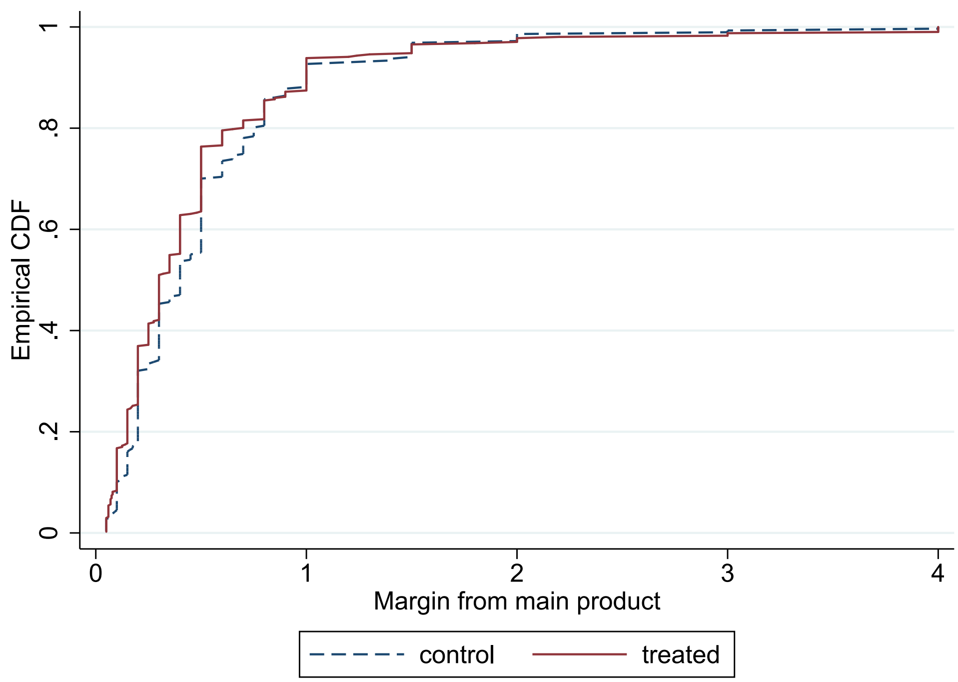
Low technology	Higher technology component
Bullock Cart	Motor Bike
Wheelbarrow	Lorry
	Tree wheeler
	Van
Other durables	
Clock	Refrigerator
Wedding reception equipment	Oven
Almera	Gas Cooker
Iron tools	Rice Cooker
Petrol max	Showcase
Bell	Blender
Plastic Chairs	Fan
Rig foam boxes	Roll Cage
Gas cylinder	Steamer iron board
Pipe rings	Beater
Tent material	Lathe work
Rotti stone	Phones
Boxer wheel	Lightmeter
Plastic racks	Furnance
Fiber related other assets	Radio
Nameboards	
Workers	
Eylashes	
Barrels	
Cement tank	
Flower pot comoflauge nets	
Oxygen Cylinders	
Roofing sheets	
Fishing hooks	

Table A.26: **TFP Effects: Separate by location of the business (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						
Treated × business at home	0.09	0.05	0.07	0.11	0.14**	0.08
	(0.06)	(0.08)	(0.07)	(0.07)	(0.06)	(0.07)
Treated × business in other location	0.06	-0.06	0.07	0.10	0.09	0.10
	(0.07)	(0.13)	(0.08)	(0.08)	(0.07)	(0.07)
Business at home	-0.11	-0.07	-0.07	-0.07	-0.13	-0.12
	(0.08)	(0.13)	(0.08)	(0.09)	(0.09)	(0.08)
Observations	2304	2304	2304	2304	2304	2304
Microenterprises	382	382	382	382	382	382
Treatments equal (p)	0.75	0.47	0.96	0.93	0.60	0.84
Treatments zero (p)	0.26	0.72	0.47	0.13	0.04	0.25
B. Dependent variable: log(TFP) estimated using Wooldridge estimator						
Treated × business at home	0.08	0.03	0.08	0.10	0.12**	0.06
	(0.05)	(0.09)	(0.07)	(0.07)	(0.06)	(0.06)
Treated × business in other location	0.05	-0.07	0.07	0.10	0.09	0.12*
	(0.07)	(0.13)	(0.08)	(0.07)	(0.07)	(0.07)
Business at home	-0.09	-0.08	-0.06	-0.06	-0.10	-0.09
	(0.07)	(0.14)	(0.08)	(0.09)	(0.09)	(0.07)
Observations	2304	2304	2304	2304	2304	2304
Microenterprises	382	382	382	382	382	382
Treatments equal (p)	0.79	0.55	0.92	0.99	0.75	0.53
Treatments zero (p)	0.27	0.83	0.36	0.15	0.05	0.14
C. Dependent variable: log(revenue/hours worked)						
Treated × business at home	0.06	0.02	0.05	0.08*	0.06	0.03
	(0.05)	(0.06)	(0.04)	(0.04)	(0.04)	(0.05)
Treated × business in other location	0.06	0.00	0.06	0.10*	0.08	0.12**
	(0.06)	(0.07)	(0.05)	(0.06)	(0.06)	(0.06)
Business at home	-0.02	-0.01	0.02	0.00	-0.02	-0.01
	(0.06)	(0.08)	(0.04)	(0.05)	(0.05)	(0.06)
Observations	2304	2304	2304	2304	2304	2304
Microenterprises	382	382	382	382	382	382
Treatments equal (p)	0.96	0.86	0.89	0.73	0.77	0.22
Treatments zero (p)	0.29	0.95	0.33	0.04	0.10	0.07

Note: This table reports tests for heterogeneous treatment effects by the location of the business on productivity, 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) estimator. 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.

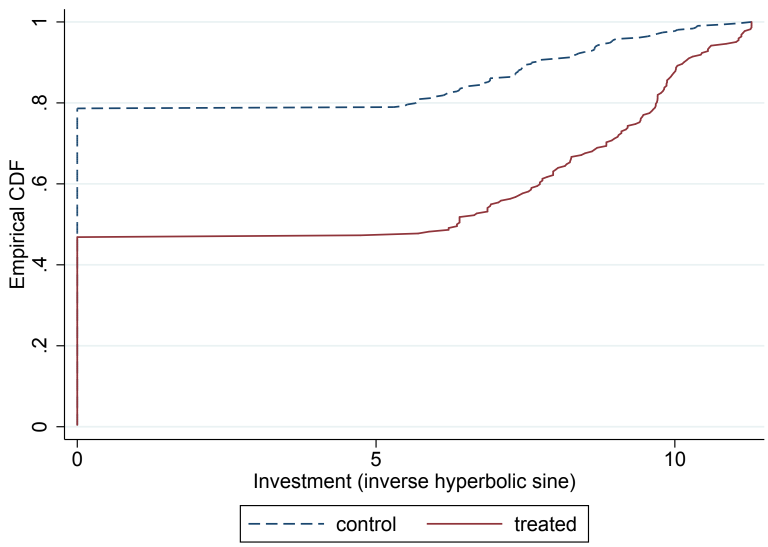
Figure A.1: **Effects on sales margins (Sri Lanka)**



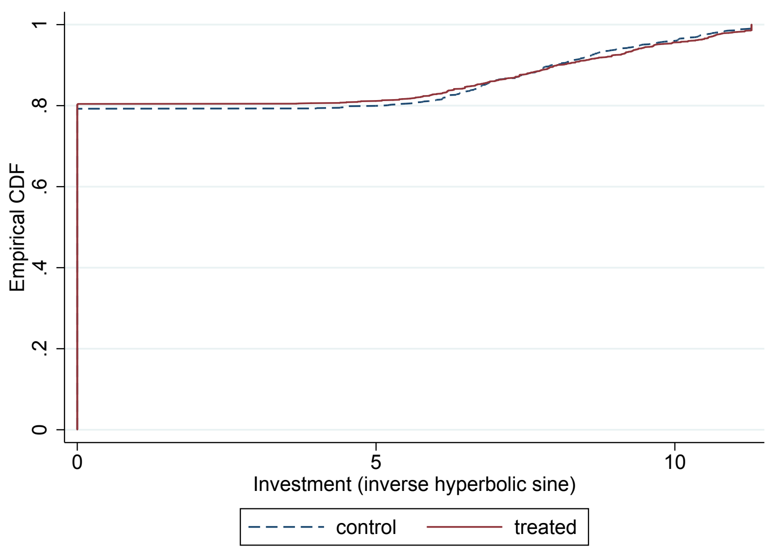
Note: CDFs of sales margins for the most important product, separate by treatment and control. Data from Sri Lanka, survey waves 7 and 8. Wilcoxon rank-sum test of equality of distribution p-values: 0.0196.

Figure A.2: **Investments upon treatment and follow-up investments (Sri Lanka)**

(a) CDF of investment upon treatment

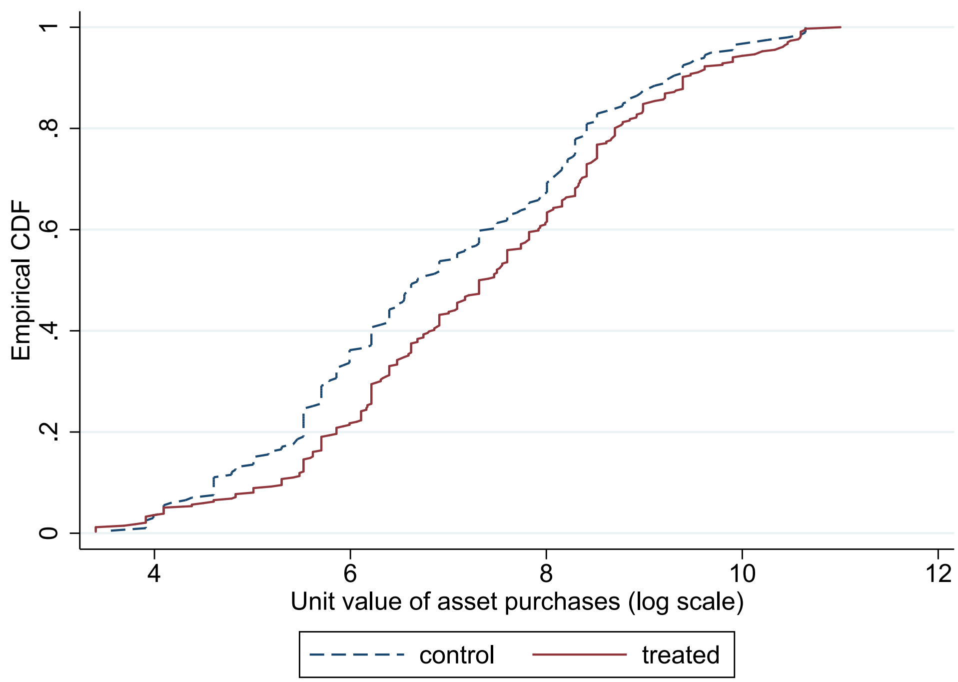


(b) CDF of follow-up investment



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.3: **Unit value of new asset purchases (Sri Lanka)**



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.