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. 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. Although long-run estimates are noisy, point estimates indicate that these productivity effects are sustained six years after the grants.

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1 Introduction

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

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

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

Building on this 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. This mechanism is known in the growth literature as capital-embodied technical progress (Solow, 1959). 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 which 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. The change in the asset composition also 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 test whether these results are sustained in the long term. In Sri Lanka, where follow-up data are available six years after the experiment, we find that the increase in TFP and capital, and the tilt in the composition of fixed business assets, is similar five to six years after the experiment as in the first year. Although long-run estimates are noisy – and thus indistinguishable from either short-run estimates or from zero – at a minimum this suggests that capital grants may have moved firms to a new trajectory with higher productivity and higher fixed capital, driven by a shift towards capital vintages with more embedded productivity. By contrast, we find that firms disinvest rapidly the stock of intermediate materials and goods that they purchased upon receipt of the grant. Even though the most striking short-run effects are a big increase in such intermediates, they cannot account for long-run impacts on the firm.

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, Karlan, and Schoar, 2018; Atkin, Khandelwal, and Osman, 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 is not directly measured 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) 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, enabling us to test how an intervention affects microenterprise productivity.

Second, we show that capital-embodied technology is a 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, Khandelwal, and Osman, 2017; Karlan, Knight, and Udry, 2015; Bloom, Eifert, Mahajan, McKenzie, and Roberts, 2013; Conley and Udry, 2010).

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 gives some economic interpretation to our results. Section 7 concludes.

[1] The two only exceptions we are aware of are Atkin, Khandelwal, and Osman (2017) 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).

2 Data and Experiments

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

The Sri Lanka Microenterprise Survey was collected for the seminal work of de Mel, McKenzie, and Woodruff (2008). It spans a representative sample of 385 microenterprises, with a capital stock of less than 100,000 LKR (about $1000), in the manufacturing, retail and service sectors. About 30% of the sample are engaged in artisan 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. 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 (and, for a second set of firms, the third wave), half of the eligible firms were randomly assigned a cash or in-kind grant of either LKR 10,000 or LKR 20,000. The in-kind grants were purchased by the enumerators according to the free choice of the firm owners and could be spent on either or both of inventory and fixed assets. The smaller LKR 10,000 grants correspond to around three months of median profits and around 55% of the median capital stock in the base period. Relevant for the issue of technological upgrading, even the cash grants were used to purchase new materials or equipment, suggesting that owners expected positive returns to these items. On average, 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, McKenzie, Quinn, and Woodruff (2014). FMQW surveyed 793 microenterprises, without paid employees or a motorised vehicle, in Accra and the neighbouring port town of Tema. These firms operate in similar sectors as those in Sri Lanka. About 40% are traders, about a third are engaged in artisan food an clothing manufacturing, and the remainder work in service occupations such as repairs or beauty salons. 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] Capital grants were randomly allocated after the second and the third wave; and for a small group, after the fourth wave. The grant size was GHC 150, or about $120. Again, grants were either in cash or in kind, but unlike in Sri Lanka, there was no variation in the grant size. The grants are comparable in size to the smaller grants in Sri Lanka. They amount to two months of median baseline profits. 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.

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

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

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 nature of the production process, 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. 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, McKenzie, and Woodruff, 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.

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

[5] 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 bounding exercise as part of our robustness checks.

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

shortcomings in the context of microenterprise production functions.

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

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

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

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

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

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

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

Dynamic linear panel methods exploit lags of output and input variables as instruments for endogenous inputs in a GMM framework. The main assumption of this class of estimator is that suitably lagged past input choices are independent of ω_{it}, but informative of current input choices due to adjustment costs, factor constraints, and other dynamic channels (Arellano and Bond, 1991; Blundell and Bond, 1998). 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.[7]

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

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

resulting GMM moment conditions are then implied by structural assumptions about input choices (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009).[8] The key economic assumption is invertibility, which requires that flexible inputs (such as materials) respond freely and monotonically to the current productivity shock, such that they can be used as a proxy for productivity. Although one might, on conceptual grounds, expect measurement error and financial constraints to pose a challenge to invertibility for microenterprises, we show that the choice of estimator makes very little practical difference for production function estimates and for the estimates of productivity effects of capital grants in this context.

A third approach commonly used does not try to identify the production function coefficients β_k, β_l and β_m in a first stage, but rather defines productivity as labour productivity, by rewriting (2) in terms of $\log(Y/L)$ (for a recent example of this approach, see Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten, and Van Reenen (2018)). This model is then augmented by the variable of interest – in our case, an indicator whether a firm has received experimental treatment in form of a capital grant – and estimated by OLS regression of labour productivity on treatment, controlling for the other production factors.

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

3.2 Production function estimates

We present the main estimates for gross output production functions of microenterprises in Table 1. We estimate separately for Sri Lanka and Ghana. In columns 1 and 3, we report the estimates from the Blundell and Bond (1998) estimator, in which lagged variables serve as instruments for endogenous inputs in both levels and difference equations. The dynamic nature of productivity leads to the inclusion of the lagged dependent variable in the estimating equation. Various specification tests are informative about how to specify the lag structure, as well as to which degree lagged inputs are relevant instruments. Appendix B discusses this in more detail. In columns 2 and 4, we report results from the control function estimator, for comparison. These are obtained using the Wooldridge (2009) implementation of the control function approach proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003), which is robust to the functional dependence problem identified by Ackerberg, Caves, and Frazer (2015).

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

< Table 1 here. >

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

Even before we turn to the TFP analysis, there are two important points worth noting about these estimates. First, the parameters are remarkably similar between Ghana and Sri Lanka.[9] In this sense, our results speak to the issue of external validity and generalisability across experimental sites. They suggest that the similarity in reduced-form results between DMW and FMQW owes much to a deeper structural similarity in microenterprise production functions across contexts. Second, our estimates are broadly similar to production function estimates for larger establishments in developing countries. Specifically, we consider estimates for medium to large plants in Chile (Pavcnik, 2002; Gandhi, Navarro, and Rivers, 2016), Colombia (Gandhi, Navarro, and Rivers, 2016) and Ghana (Söderbom and Teal, 2004). We obtain approximately similar coefficient magnitudes as for those larger firms, and the same relative ordering of coefficient size that is commonly found in that literature ($\beta_m > \beta_l \geq \beta_k$).

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

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

Second, 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.

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:

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

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

Table 2 presents our main result, for the three standard productivity measures: TFP from a Blundell and Bond (1998) estimation, TFP from a control function estimator (here, Wooldridge (2009)) and labour productivity expressed as revenue over total hours. As noted earlier, our third approach does not require any production function estimation, bur rather uses capital and materials inputs as control variables in the outcomes regression. We estimate productivity effects at the mean, and at various quantiles of the distribution. We pool across samples from Ghana and Sri Lanka to maximise statistical power. Our regressions include survey wave and industry controls, separately by country, and control for baseline values of the dependent variable.

< Table 2 here. >

Our results are remarkably stable across the three outcomes. We find that treatment increases productivity significantly by 5-6 percent on average, as well as at the median. We find particularly an outward shift at the top of the distribution: productivity increases by 7-9 percent at the 80th percentile. We 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. 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 ($p = 0.01$) and also for Sri Lanka ($p = 0.07$).[10]

< Figure 1 here. >

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

4.2 Robustness of TFP effects

We assess robustness of our findings in various ways. To begin with, note that our headline results are already based on a variety of productivity measures and estimation techniques. Instead of picking a single technique, we use from the outset all three of the common families of approaches to productivity estimation. We obtain quantitatively and qualitatively very similar results across all the approaches. Moreover, we document robust effects not only at the mean, but also at various points of the distribution; and we test for equality of the entire distributions in a non-parametric way. All of this should give us confidence that we pick up a common signal about productivity across these measurements.

Nevertheless, we conduct a number of further robustness exercises. We summarise the results here, and show 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 additional 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 methods, other than the three most common methods that we utilised 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

[10] 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.

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 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.16 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.17 and A.18). We find very similar patterns in both countries, with TFP increases in the upper part of the distribution.[11]

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. However, the available data are inconsistent with such an interpretation. While there is no direct information on prices which would allow us to construct physical productivity (TFPQ), information on sales margins for the main product is available in two waves of the survey.[12] 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 this paper,

[11] 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.17 and A.18 – 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.) Taking into account the non-parametric evidence which showed a significant improvement in TFP for treated forms (and strongly so in Ghana), we conclude that treatment has shifted TFP in both countries in a similar way.

[12] 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?"

we nevertheless test for gender heterogeneity in TFP effects in both datasets. Our results (in Tables A.19 and A.20) are inconclusive, and we note that our tests have low power. We find suggestive evidence of higher treatment effects for men in Sri Lanka, and for women in Ghana. However, we note that we cannot reject the null hypothesis of equal treatment effects across gender in either setting. In Ghana, we also find some evidence that TFP effects are higher for in-kind treatments.[13] These results add a complementary perspective to the 'flypaper effect' for female microenterprise profits reported by FMQW.

5 Mechanisms

5.1 What kind of capital do capital grants buy?

After documenting the effects of capital grants on residual TFP, 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.[14]

For evidence on this mechanism, we turn to the detailed listing of capital assets in the questionnaire from DMW in Sri Lanka.[15] The questionnaire lists individual business assets with their name and replacement value, within the following categories: 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 make use of these categories, which we assume aggregate individual asset items by their functional role in the business, as determined by the business owner. We then examine which types of capital goods treated firms invested in.

[13] These results are in Appendix Table A.21. For Sri Lanka, we cannot reject the null hypothesis that cash and in-kind treatments have the same effect (Appendix Table A.22). The point estimates are somewhat higher for cash treatments.

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

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

Theory, however, does not give us clear predictions which functional categories of capital should embody technology. Will treated firms invest into more recent vintages of machines, replacing older vintages with new ones? Or will they invest into new types of assets they have not previously used in their business? In order to examine directly the role of technology embodied in assets, we additionally hand-code individual items according to whether they have a more advanced technology component. In our context of Sri Lankan microenterprises, these tend to be powered tools, or items made out of better material than older vintages. The more technologically advanced assets generally serve a similar purpose and are useful in similar activities and industries as their less technology-intensive 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. The full list of items in each category can be found in Appendix Table A.25.

< Table 3 here. >

We find that microenterprises in the treatment group acquire different assets than the control group, and that those assets are technologically more advanced. Table 3 displays the effects of capital grants on different categories of microenterprise capital. As before, we report coefficients on treatment dummy from ANCOVA regressions. 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.[16]

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 core to running the firm – such as machinery, which comprises almost half of the average capital stock in control firms. Instead, treated firms acquire assets that previously played a more marginal role: vehicles and other durables goods. We show this in Figure 2, which graphs this extensive margin of asset ownership over time for the treatment and control

[16] In Appendix Table A.24 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.

groups. At baseline, 90% of all firms own assets in the categories tools, machinery or furniture. 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. We therefore call these assets 'essential' for the business. 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. Over the course of nine survey waves, this wedge remains essentially constant.

< Figure 2 here. >

Detailed qualitative evidence on the type of assets purchased gives us another angle to understand how capital grants change the composition of capital. Among the most commonly purchased assets in the treatment group are vehicles, refrigerators, and showcases.[17] 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 engange in. But they can allow business owners to carry out their activities much more effectively – and perhaps even in qualitatively different ways that reaches new market segments. We therefore turn to examining how treated firms change their way of doing business.

5.2 Changes in doing business

To sum up our key results so far: we found that capital grants increase microenterprise TFP, and we have shown that capital grants increase firm capital in a non-homothetic way, tilting its composition towards non-essential categories of capital, and assets with a higher technology component. This suggests capital-embodied productivity as a mechanism behind the TFP increase. We now turn to more direct evidence that connects these two findings, and gives us further confidence in interpreting them as evidence for the mechanism. We acknowledge, of course, that we will not be able to pin down all the possible ways in which these heterogeneous firms make use of their assets. Nonetheless, we view this exercise as a useful illustration how, in concrete ways, capital can sustain productivity increases.

< Table 4 here. >

[17] These items are much less commonly purchased by the control group. Even though the absolute number of cases for each specific item are small, 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.

In Table 4, we report the effects of treatment on a range of different indicators of how firms do their business. The first three columns show effects on the product and market scope. Treated firms were able to increase their customer base by about 20%, or two customers a day. We find a similar increase in the likelihood of introducing a new production, although this is not statistically significant. Finally, new products are of great importance for treated firms, in the sense that they constitute approximately a 20% larger share of overall sales for treated firms.[18]

Since a large share of firms in our sample are retail firms, a natural question that arises is how to interpret these findings, and increases in retail TFP more generally.[19] We lack detailed data on product prices from firms in our setting. The best we can do is to look at the sales margins from the main product (in Appendix Figure A.1) that we discussed in earlier parts of the paper. Our finding that sales margins are lower at treated firms suggests that treated stores may indeed have used their improved productivity to lower their prices. This is consistent with the result in Atkin, Faber, and Gonzalez-Navarro (2018) – who show that, in the case of foreign supermarket entry in Mexico, welfare gains from productivity increases in retail mainly arise through lower prices consumers pay at affected stores, which pass through some of their productivity advantages.

Even though the firms in our sample – like in most studies on firms – are very heterogeneous and so are their business practices, the data offer some illustrative evidence how firms that adopt more technological capital can change their way of doing business. Refrigerators are the single most commonly purchased asset among treated firms (still, fewer than 1% of all treated firms acquire one). Refrigerators allow firms to produce or trade products that require cold storage, or that are easily perishable in the tropical heat. This could have two types of impacts on firms: they could introduce new products they previously did not carry, or they could reduce spoilage and hence the running costs of their business. Columns (3) to (5) of Table 4 show that treated firms are significantly more likely to introduce refrigerated and perishable products. The relative magnitude of these effects is large – a tripling and doubling, respectively, relative to the control group. The absolute magnitude of this effect over the entire sample is of course low, and reflects the share of all firms that adopt refrigerators. We find no effect on reducing spoilage of goods (Column (6)).

[18] The absolute effect size and control mean of this outcome are low, since firms without a new product introduction have by definition zero sales from new products.

[19] Specifically, they could simply reflect the possibility that demand and profits shift from one retail shop to the other, without any aggregate welfare gains. The possibility of such spillovers could raise concerns about a violation of the stable unit treatment value (SUTVA) assumption underlying experimental program evaluation, in both our work and in the original research papers based on the same experiments. The experimental design in DMW and FMQW, however, foresaw the possibility of such issues, and deliberately constructed a geographically dispersed sampling frame in order to minimise spillovers to close control units. In both contexts, the experimental sample is small compared to the universe of microenterprises in the market; spillovers through market-level price adjustments are therefore unlikely to be of concern.

These results suggest a potential explanation for why we find that productivity effects of capital grants come from the upper half of the distribution. If it is more generally true that such productivity effects are achieved by improvements in processes, expansion into new markets, and product innovation, then we would expect firms that are relatively more productive at baseline to be more likely to turn new capital into higher productivity. In other words, the more able and innovative entrepreneurs will be able to make especially good use of their novel assets, whereas the less able entrepreneurs will not.

We further test whether the results are a consequence of entrepreneurs moving into completely new lines of business, or of moving location (for example, from street hawking to fixed premises). It is not immediately obvious from the theory of embodied technology growth that firms should change their line of business – indeed, the main narrative of the theory is that newer capital vintages allow firms to do the same activity more effectively. Consistent with this, we find no effects on either of these two outcomes, with estimates shown in Columns (7) and (8).

An alternative interpretation of these findings 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. As noted earlier, this is not our finding here. 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 bound to the true effects of capital-embodied productivity.[20] 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).

Finally, to study potential capital lumpiness, we look at the unit prices of asset purchases. Treated firms acquire somewhat more expensive assets after receiving capital grants (see Appendix Figure A.3). Treated microenterprises are also more likely to purchase 'big ticket items'. For instance, a third of treated firms purchased an item with unit value of more than 40 USD (roughly the average monthly profit at baseline), but only 18% of control firms.[21] On the other hand, even at baseline, about half of the firms at least one individual item worth 40 USD or more. If the lumpiness of capital is a reason why

[20] 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 6).

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

control firms do not buy productivity-enhancing assets, then this must be a constraint at the margin, not a constraint for the average capital stock of microenterprises.

6 Implications

6.1 Are productivity and capital effects sustained over time?

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

We turn to the long-term follow up data for Sri Lanka to assess whether productivity improvements and shifts in the asset composition are sustained over time. de Mel, McKenzie, and Woodruff (2012) report a sustained increase in profits for the treatment group more than six years after the initial capital grants.[22] In Table 5 we include these long-term follow-up surveys into our data, and report dynamic treatment effects separately by the year since the capital grant was given. We find that TFP, fixed capital, as well as the tilt in the capital composition are sustained throughout the years. About six years after the intervention, estimates for each of these outcomes are similar or even larger to those in the first year after treatment; although the long-term data are much noisier, such that no individual coefficient at this horizon is statistically significant. However, year-by-year treatment effects up to three years post-treatment are of similar magnitude and mostly individually significant.

< Table 5 here. >

Where we do find significant disinvestment over time is in the stock of goods and materials that the firms hold in inventory. Firms decapitalise inventories quickly after the first year, such that stocks in any subsequent year revert back to the level of the control group. This evidence suggests that the most profound change in microenterprises

[22] 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.

immediately after treatment – a strong increase in inventories, which account for two thirds of business purchases from the grants – cannot explain the sustained increase in productivity and profits. This rules out an alternative explanation that productivity effects in this context are driven by a higher level inventories, for example through reduced stock-outs, better customer choice, or lower re-stocking costs potentially associated with higher inventories stocks. Rather, this pattern of results over time again points to technology-embodied capital as the channel.

If entrepreneurs do not have immediate full knowledge of the productivity effects of investing into new, productivity-enhancing assets, they might be reluctant to try out a risky investment (Atkin, Khandelwal, and Osman, 2017; Conley and Udry, 2010). While durables, vehicles and other assets with higher technology components as well as TFP increase immediately upon grant receipt, there is no catch-up from the control group. This suggests that the windfall from grants allowed individuals to purchase assets that they would otherwise not have acquired. 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). Similarly, as we showed in Figure 2, control firms do not acquire the same productivity-enhancing assets as the treatment group: even three years after the grants, the initial differences in vehicles and durables ownership that opened up between the treated and control microenterprises prevails.

6.2 How important are the productivity effects of capital grants?

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

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

where $a_{it} = \ln A_{it}$ is the log of TFP and z is treatment status (which in our case is binary).[23] Equation 4 breaks down the revenue effects of capital grants into the contributions associated with adjustments to production factors, and changes in TFP. Replacing population quantities with sample analogues (our estimated coefficients of the production function, and estimated treatment effects on inputs and TFP) lets us immediately compute this decomposition.

[23] 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.

We report the results from the decomposition in Table 6. 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.[24] We find that changes in TFP account for 19-29% of the treatment effect of capital grants on revenues in Sri Lanka, and 21-35% in Ghana. The increase in capital stock accounts for about 20% on average, and higher material use contributes on average to around 50% of the increase in revenues. The contribution of changes to labour input on revenues is negligible.[25]

< Table 6 here. >

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

7 Conclusion

In this article, we look at microenterprises through the structural lens of a production function. We robustly estimate production functions to microenterprises using an array of standard methods. This enables us to analyse the effects of capital grants on productivity. We find that capital grants to microenterprises in Sri Lanka and Ghana have significant and lasting effects on total factor productivity. A decomposition analysis suggests that returns to capital grants for microenterprises contain a significant return to increased productivity. This adds a more nuanced interpretation to the previous assumption in this literature that treatment effects are returns to capital alone.

We find evidence for a plausible mechanism behind this: capital items that embody superior technology allow firms to improve total factor productivity. Treated firms acquire

[24] 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

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

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.

These findings speak to a broader policy debate on how to address the persistence of small informal firms in developing countries (Hsieh and Klenow, 2009; Meghir, Narita, and Robin, 2015; Ulyssea, 2018). They also suggest that capital grants – in particular, the provision of more technologically advanced assets that support microenterprises in their existing lines of business – can be a policy tool to improve productivity of firms which are located of the bottom of the economy-wide productivity distribution.

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Tables and Figures

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

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

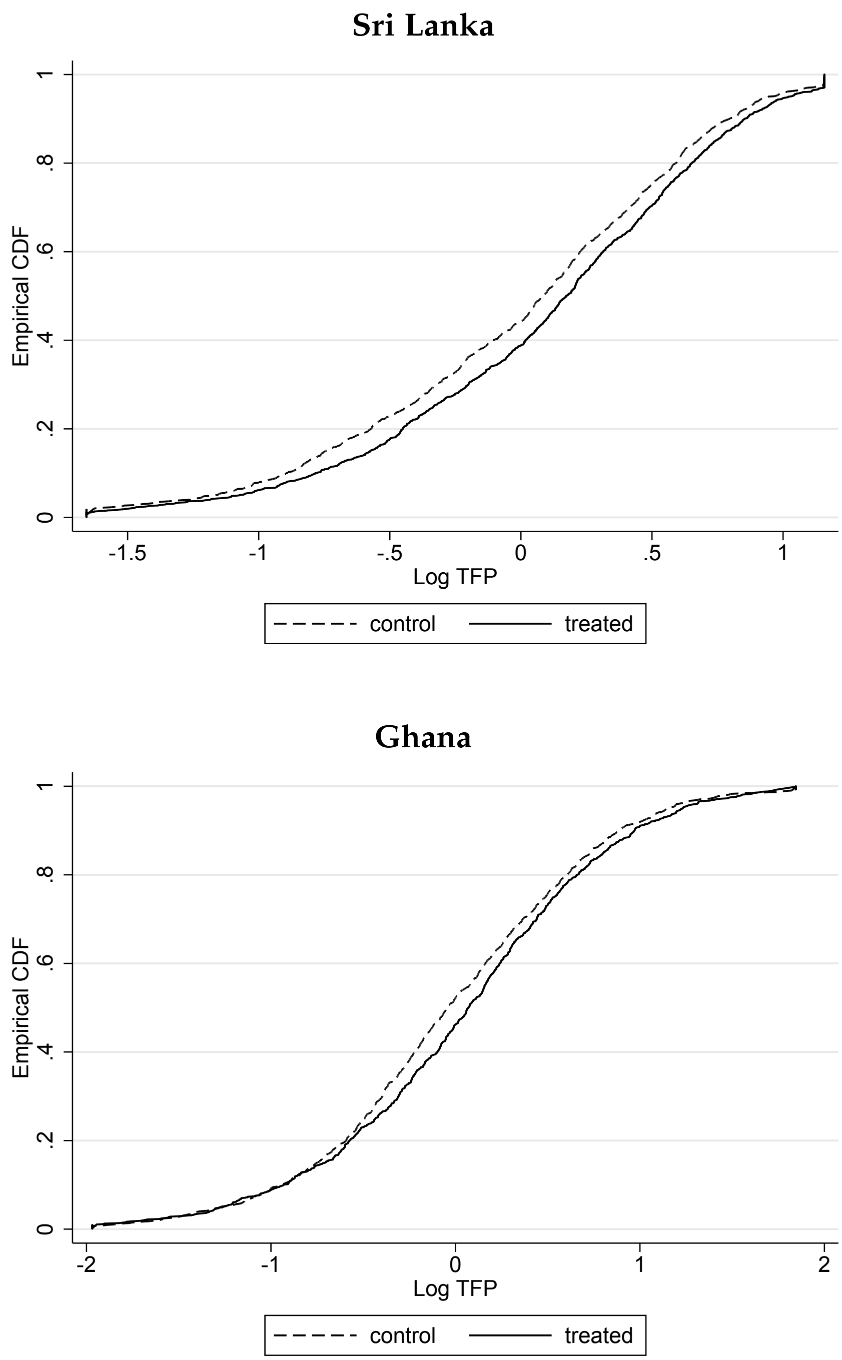
Note: Estimators employed are Blundell and Bond (1998) System GMM and the Wooldridge (2009) control function estimator. All models partial out for wave dummies and post-treatment status (not reported). We report p-values for the Hansen (1982) test of over-identifying restrictions, the Arellano and Bond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

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

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

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

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



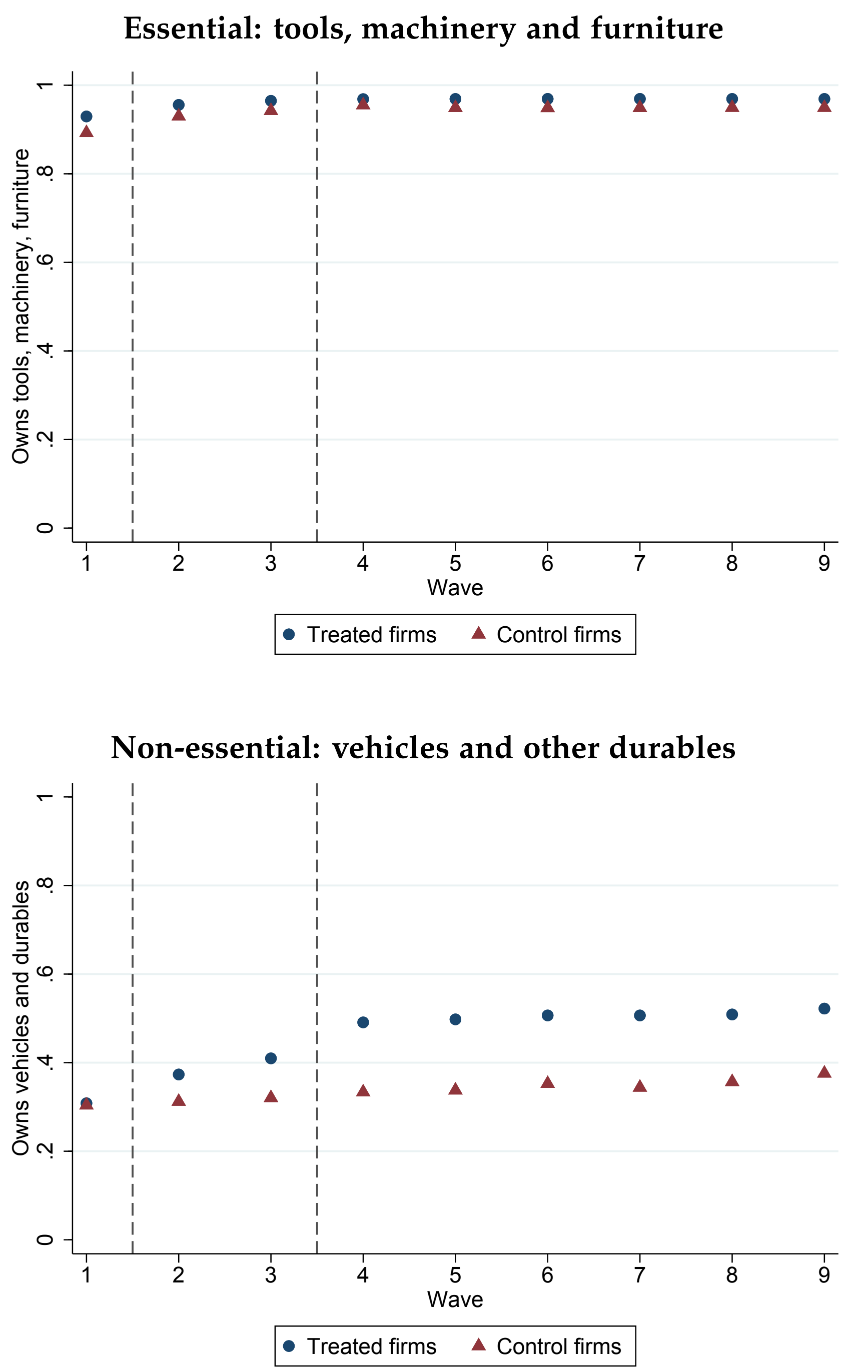
Note: CDFs of TFP for treated and untreated microenterprises in the waves after treatment was administered. Wilcoxon rank-sum test of equality of distribution p-values: 0.07 (Sri Lanka) and 0.01 (Ghana).

Table 3: **Effects of capital grants on microenterprise capital**

	(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**



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 4: **Effects of capital grants on business practices, market and product scope**

	(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.

Table 5: **Long-term effects of capital grants on productivity, capital, and intermediate inputs**

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

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

Table 6: **Decomposing the effect of capital grants on revenue**

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

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

Online Appendix

A Data construction

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

Revenue (output) is the total sales 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[26] 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

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

(1998) estimation tends to be informed by empirical specification tests, not by a priori assumptions about the structure of production process in the firm. Our choice of lag structure is informed by three such specification tests. First, since the model includes many more instruments than endogenous regressors, the Hansen (1982) test of overidentifying restrictions helps judge the validity of the moment conditions. Under the null hypothesis that the moment conditions hold, the test statistic follows an asymptotic chi-squared distribution. Hence the test passes if we do not reject the null.

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

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

Our choice of lag structure in Table 1 is informed by these three sets of test, by coefficient stability in Appendix Tables A.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, Caves, and Frazer (2015), and Wooldridge (2009). The strategy essentially amounts to introducing a control function term into equation (2): most commonly, a lagged polynomial of flexible inputs and capital. The resulting GMM moment conditions are then implied by structural assumptions about input choices. The key economic assumption is invertibility, which requires that flexible inputs (such as materials) respond freely and monotonically to the current productivity shock, such that they can be used as a proxy for productivity. This requires the absence of any constraints to material input use, such as credit constraints. A second assumption that control function estimators need to make for invertibility to hold is the absence of measurement error in inputs, specifically in materials.[27]

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

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

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

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

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

and the instruments are given by:

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

[27] 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, Caves, and Frazer (2015) in column (8) of Tables A.2 and A.5.

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, Caves, and Frazer (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, Caves, and Frazer (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**

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

Note: This table reports the effect of treatment on TFP at different moments of the distribution, for microenterprises in Ghana and Sri Lanka. In Panel A, TFP is estimated using the Blundell and Bond (1998) System GMM estimator. In Panel B, TFP is estimated using the Wooldridge (2009) 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.9: **TFP Effects: Alternative production function estimators**

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)**

	(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 5% per year**

	(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 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, the dependent variable is the standard measure of labor productivity. All regressions include wave-times-survey and industry-times-country fixed effects.

Table A.13: **TFP effects: Assumed depreciation 10% per year**

	(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 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, 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 15% per year**

	(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 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, 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 20% per year**

	(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 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, 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: Assumed depreciation 25% per year**

	(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 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, the dependent variable is the standard measure of labor productivity. All regressions include wave-times-survey and industry-times-country fixed effects.

Table A.17: **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.18: **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.19: **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.20: **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.21: **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.22: **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.23: **TFP effects: Lee Bounds on non-response and attrition**

	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 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.24: **Effects of grants on capital: intensive and extensive margin by category**

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

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

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**

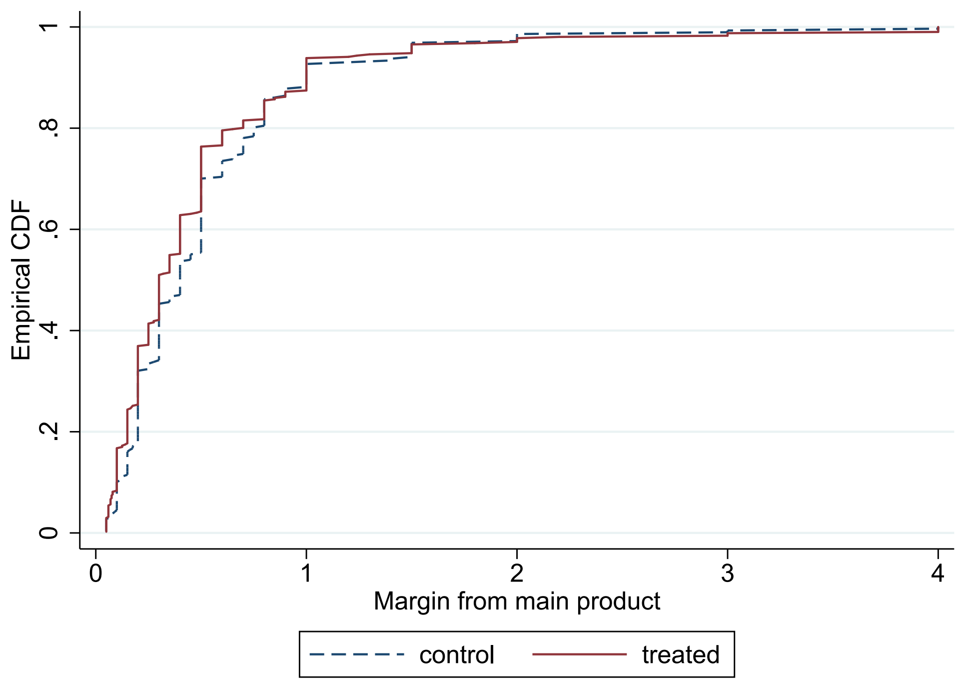
Low technology	Higher technology component
Bullock Cart	Motor Bike
Wheelbarrow	Lorry
	Tree wheeler
	Van
Other durables	
Clock	Refrigerator
Wedding reception equipment	Oven
Almera	Gas Cooker
Iron tools	Rice Cooker
Petrol max	Showcase
Bell	Blender
Plastic Chairs	Fan
Rig foam boxes	Roll Cage
Gas cylinder	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.

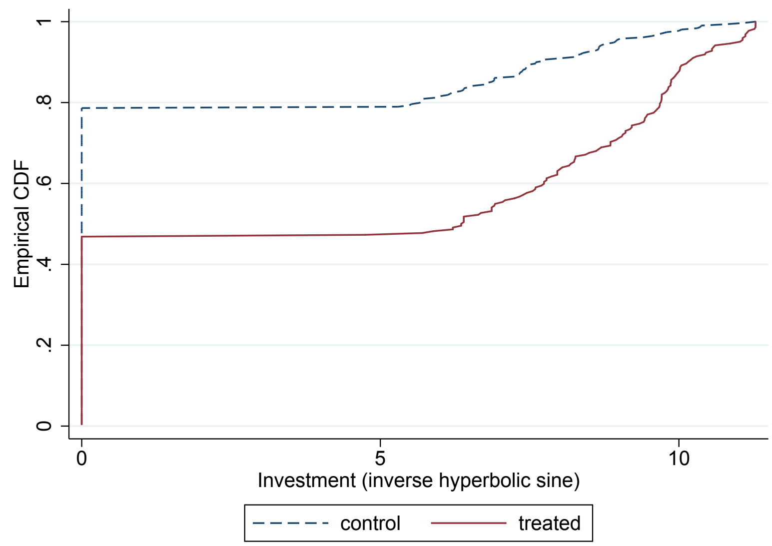
Figure A.1: **Effects on sales margins**



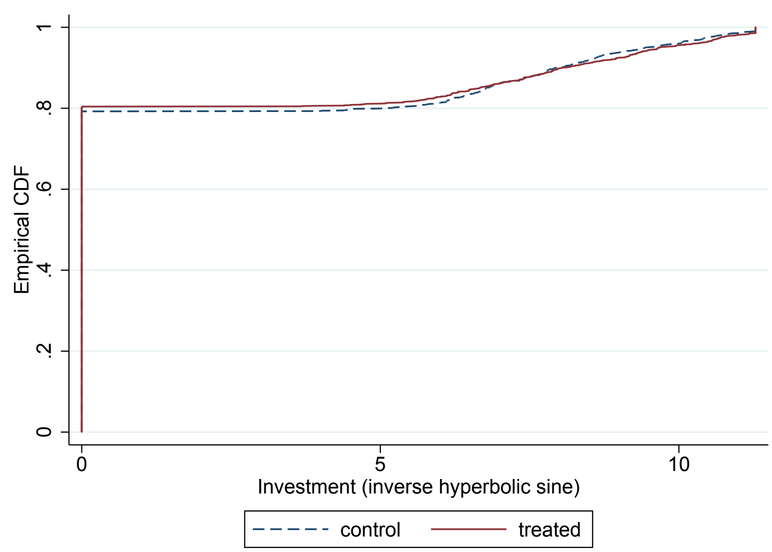
Note: CDFs of sales margins for the most important product, separate by treatment and control. Data from Sri Lanka, survey waves 7 and 8. Wilcoxon rank-sum test of equality of distribution p-values: 0.0196.

Figure A.2: **Investments upon treatment and follow-up investments**

(a) CDF of investment upon treatment

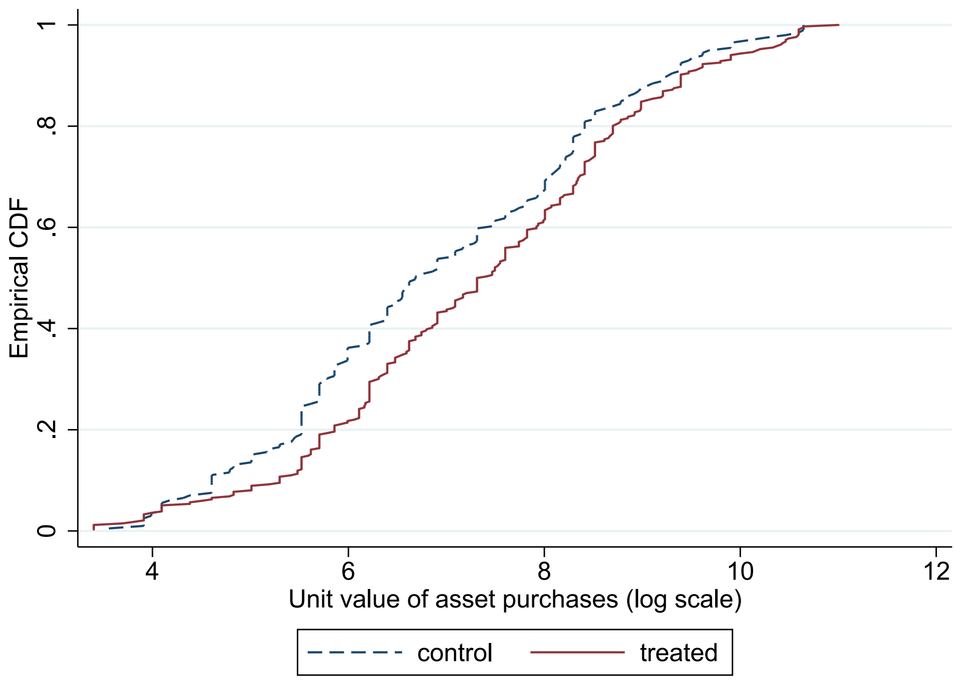


(b) CDF of follow-up investment



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**



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.