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Can capital grants help microenterprises reach the productivity level of SMEs? Evidence from an experiment in Sri Lanka.*

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Abstract

Using data from a randomized control trial in Sri Lanka, this paper explores whether cash and in-kind grants helped microenterprises approach the productivity level of SMEs. The paper first estimates production functions and subsequently treatment effects on TFP levels. Most significantly, more able and more risk-averse owners benefit from the larger in-kind grant. Also, the larger in-kind grants allowed for increases in productivity to the least productive firms. The paper then uses data from a representative sample of formal firms to put the TFP levels and treatment effects in the microenterprises into perspective. The results suggest that the least productive firms where able to catch up with the average microenterprise and formal SMEs, while a gap remains with large firms. This finding encourages a positive view of the potential for productivity growth in microenterprises.

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

Keywords: Economic development, microenterprises, formal informal, total factor productivity, embodied technology

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1 Introduction

Microenterprises (MEs) are important sources of employment and income in developing countries where large formal firms are often scarce and underdeveloped. Microfinance institutions and unconditional cash transfer programs aim to support the expansion of these informal firms by alleviating credit constraints that have long been suggested to be one of the main constraints to their growth (Banerjee, 2001; Banerjee and Duflo, 2005). A recent series of experiments have investigated the effects of cash and equipment drops on informal firm profits, with often positive and significant results, especially for male recipients. A seminal study in this literature was an experiment conducted in Sri Lanka by De Mel, McKenzie and Woodruff (2008) (DMW henceforth). The authors find large returns to capital drops both in the form of cash and in-kind that persist several years after the intervention (de Mel, McKenzie, and Woodruff, 2012). This result has since been replicated in various settings (Fafchamps et al., 2011a; Martínez, Puentes, and Ruiz-Tagle, 2012).

The expansion of firms due to the reduction of capital constraints can be the result of two distinct processes. First, the capital drop may allow the firm to more rapidly approach its steady state capital and profit level. This level may still be very low and the enterprise may remain firmly at a very small scale. A recent experiment in Chile (Martínez, Puentes, and Ruiz-Tagle, 2012) finds that returns are largest for individuals who have been initially unemployed and diminish rapidly both with size of the capital drop and the initial firm size. Alternatively, the reduction of liquidity constraints may allow a firm to expand its level of productivity for example by introducing more advanced equipment or materials and thus more efficient means of production.

This process, the introduction of technology embodied in capital has been found to be of paramount importance in formal firms both in developing (Radosevic, 1999; Kathuria, 2000) as well as developed countries (Papaconstantinou, Sakurai, and Wyckoff, 1996; Sakellaris and Wilson, 2004). Relative to an increase in capital with constant technology (through a replication of the existent stock) which runs into diminishing returns, an increase in productivity can initiate a sustained expansion of firms. This process would be of great importance for the transformation of the informal sector in developing countries, which has been repeatedly found to be highly unproductive and stagnating (Liedholm, 2002; Hsieh and Klenow, 2009; Rijkers et al., 2013; Nichter and Goldmark, 2009). Clearly, productivity is not only constrained by an inability to purchase more advanced equipment and thus more efficient production methods. Hypothesis concerning the factors that constrain informal firm productivity include managerial and information constraints (Karlan and Valdivia, 2011; Bloom et al., 2013; De Mel, McKenzie, and Woodruff, 2012a) risk aversion (Field et al., 2011; Karlan, Knight, and Udry, 2012), present-bias (Fafchamps et al., 2011b; Duflo, Kremer, and Robinson, 2011), poor infrastructure and regulatory environment (Abbott, 2013) and a lack of demand (Amsden, 2010). Out of these, technology however has a potential to be addressed from outside and at the firm level. Also, several qualitative studies report that owners of small firm identify technology as an important constraint of productivity and expansion (Khundker, 1989; Aftab and Rahim, 1989; Kabecha, 1998; Abbott, 2013). If this was the case, the relaxation of capital constraints can lead to a result as observed by de Mel, McKenzie, and Woodruff (2012). The authors find after several years that the grants led to a persistent expansion of capital levels and profits. I suggest in this paper that capital drops allowed a subsample of credit constrained firms to introduce more efficient production methods and thus to permanently expand their steady state.

The natural consecutive question to ask after this finding is whether this increase in productivity allowed microenterprises to catch up with SMEs. Whether the informal sector is solely a manifestation of the economic desperation of the unemployed or a productive element of a countries economic activity has significant policy relevance. If the productivity of microenterprises significantly lags behind that of SMEs or larger enterprises, government efforts should be focused on encouraging the creation of jobs in the latter. If on the other hand the gap in productivity in the informal sector is negligible, it should be supported by policy makers as a valuable part of the economy. This is especially the case if interventions such as capital drops can improve efficiency in microenterprises.

This paper empirically investigates these issues by using the data from DMW's experiment in Sri Lanka. The study includes precise measurement of factors of production and thus allows the estimation of production functions and TFP levels. It is to my knowledge the first study that uses experimental evidence to investigate the effect of capital drops on productivity growth in microenterprises. The paper then proceeds to estimate productivity levels for a representative sample of formal Sri Lankan small, medium and large enterprises included in the World Bank Enterprise Survey (ES henceforth). This allows a comparison of productivity levels between microenterprises and firms in the formal sector.

The following results emerge from this investigation. Only those firms with more able, better educated and more risk averse owners benefit from the intervention. The evidence for this is most consistent for the large in-kind grant. Also, those starting from very low productivity levels were able to increase their productivity through the purchase of equipment, again if they received the largest in-kind grant. There is a strong overlap between the firms that increase their productivity and those which increase their profits suggesting that there is an important productivity component in the returns to capital. These results suggest a mechanism for the finding of previous studies. Capital drops for small firms can have permanent positive effects on profit levels and this is an important benefit especially for the poorest firm owners.

The comparison with formal firms from the Enterprise Surveys shows that microenterprises have productivity levels similar to those of formal SMEs. This is initially not the case for the least productive microenterprises. Importantly however these firms manage to catch up through the intervention. Unlike other studies assessing informal firms, this result offers a more optimistic view of the potential for productivity growth of microenterprises and the informal sector. Data included in the ES also suggests that a non-negligible share of formal firms originated in the informal sector and spent several years unregistered. This further supports the suggestion that informal firms can grow to become efficient and formalised.

The paper proceeds as follows. Section 2 discusses the role of embodied technology in a Ramsey model of informal firm production. Section 3 introduces the data, experiment and the empirical strategy both for the estimation of production functions and treatment effects. Section 4 reports and interprets the treatment effects on productivity in the microenterprises. Section 5 compares the productivity levels of microenterprises to those of the ES firms and puts the observed treatment effects into perspective. Sections 6 and 7 interpret these results and conclude.

2 Dynamic Firm Production with embodied technology

To formalize the analysis of TFP in informal firms and to introduce the discussion of the structural estimators and the moment conditions in section 3 consider the following modification of a standard model (e.g. Fafchamps et al. (2011b)) of the intertemporal decision making of a household with an attached microenterprise.

The entrepreneur owns two types of assets, physical capital k_t and a financial asset a_t. She earns a returns $(1+r)a_t$ on the financial asset and uses capital to produce a single good using the following production function:

$$y_t = y(k_t, l_t, \omega_t) \tag{1}$$

where k_t, l_t are the current level of capital and labour (materials are omitted for simplicity in the theoretical model but are included in the empirical specification).[2] Capital

[2]Note that human capital here is missing. In an alternative specification I have introduced a human capital variable as in e.g. Hall and Jones (1999) but it is insignificant in all specifications and was thus omitted.

moves according to a standard equation of motion:

$$k_t = (1-\delta)k_{t-1} + i_{t-1} \tag{2}$$

where i_{t-1} refers to investment at the end of the previous period. In Eq. (1) ω_t is a period specific productivity shock,[3] which is in most models assumed to be random and exogenous. However, as argued above, there is reason to believe that the entrepreneur has some choice over the technology level in her enterprise by choosing the right amount of capital and intermediate inputs and thus the productivity embodied in those inputs. A further channel that could be important in the context of the informal sector is that under credit constraints, firms may be unable to purchase materials necessary for production at the right time. In the SLMS baseline survey 34% of the interviewed firms answer that a lack of inputs constrains the size of their business. This disruption too would show in the TFP residual.

The above discussion represents a deviation from the usual model of dynamic firm production. I therefore propose the following equation for technology:

$$\omega_t = \omega^k\{k_t, \phi_t\} + \omega^e(\omega^e_{t-1}, \xi_t) \tag{3}$$

where the first term is productivity embodied in capital and the second term is an exogenous technology level which is usually assumed to follow a stationary AR(1) process, with ξ_t being the exogenous increase in productivity from period $t-1$ to t (which is usually referred to as the productivity innovation).

The catch-all variable ϕ_t captures the capacity of the firm to absorb the technology embodied in capital. The relevant literature (Keller, 1996; Zahra and George, 2002) suggests that among others this capacity depends on the education level, cognitive ability, gender and degree of risk aversion of the owner, the age of the business and the distance of the individual firm's technology level to the available technological frontier. Note that while a lower degree of risk aversion will mean that owners invest in less predictable technology, it may mean that they already have done so and the treatment may thus have no added effects. On the other hand, highly risk averse owners may initially be further away from the available technology frontier and thus benefit especially from an in-kind grant that encourages them to introduce new technology. These determinants inform the heterogeneity analysis in the empirical section.

Using this production function to generate income the microentrepreneur solves a dynamic consumption and investment problem of the following form:

[3]Note that it is convention to refer to the current level of productivity as the productivity shock, while the change in the productivity level from one period to the next is referred to as the productivity innovation.

$$\max_{c_t > 0,\ k_t \geq 0,\ a_t \geq 0} \sum_{t=0}^{\infty} \beta^t u(c_t), \text{ where } \frac{\partial u}{\partial c} > 0,\ \frac{\partial^2 u}{\partial c^2} < 0 \tag{4}$$

subject to

$$c_t = Y(k_t, l_t, \omega_t^k, \omega_t^e) - p_l l_t + (1+r)a_t - a_{t+1} + (1-\delta)k_t - k_{t+1} + z_t \tag{5}$$

where z_t is a random income shock. Investment has been rewritten as the difference between capital in the two periods. Consider the case where marginal returns to capital are still higher than the returns to the asset, so the optimal level of the asset is zero.[4] Solving for the entrepreneur's optimal choice of capital and static inputs leads to the following Euler equations:[5]

$$\frac{u'(c_t)}{u'(c_{t+1})} = \beta \frac{\partial y(k_t, l_t, \omega_t^k, \omega_t^e)}{\partial k_t} + \frac{\partial y(k_t, l_t, \omega_t^k, \omega_t^e)}{\partial \omega_t^k} \frac{\partial \omega^k(k_t, \phi_t)}{\partial k_t} + (1-\delta) \tag{6}$$

$$\frac{\partial y(k_t, l_t, \omega_t^k, \omega_t^e)}{\partial l_t} = p_l \tag{7}$$

From this model, we can obtain several important implications.

For the estimation of production functions, note that the optimal level of inputs depends on the current productivity level of the firm, which is observed by the owner at the beginning of each period. This is commonly assumed for the static inputs labour and materials, but not for the dynamic input capital. Capital is determined through investment at the end of the previous period,[6] without observing the exogenous change in productivity between t and $t+1$. In the above case however, productivity and capital are related through the potential embodied technology effect. Since the best guess for productivity in the next period is this period's productivity shock, future productivity does not enter the firm's input choice. These assumptions are translated into the relevant moment conditions in the GMM estimation of the production functions.

The above equation also suggests that the optimal choices of equipment is dependent on the response of productivity to these variables. This in turn depends on the characteristics of the firm. If there is no relationship between productivity and inputs the above conditions

[4] As soon as the capital level is high enough so that the returns to the asset are higher than the (diminishing) returns to capital, the household would invest only in the asset and the firm would reach its steady state capital level. Since there was an increase in capital even for those firms who received the cash treatment, it is likely that at least some of the firms had not reached their respective steady state (De Mel, McKenzie, and Woodruff, 2008).

[5] This is obtained by plugging the constraint into the utility function for each period and solving for the optimal level of k_t, l_t and m_t.

[6] This assumes that there is no rental market for capital which is generally consistent with the firms in the sample of De Mel, McKenzie, and Woodruff (2008)

collapse into the standard Euler equations. Given that there are capital constraints the optimal response to a capital shock will depend on characteristics captured by ϕ_t.

This gives two testable results:

Result 1: If technology is embodied in capital and capital increases in response to a random income shock, productivity will increase in the firm.

No significant increase in productivity when capital increases due to the random treatment would thus suggest that either there is no embodied technology available to the firm or the firm owner is not aware of it or unable to use it. This for example may be due to a lack of specific training or of complementary inputs. Unfortunately it is not possible to test these hypotheses given the available data.

Result 2: The increase in productivity will depend on the characteristics of the firm. More specifically, more educated, able and risk-averse firm owners with firms that have been operating for longer and those further away from the locally available technology frontier should be able to increase their productivity the most in response to the treatment.

3 The Experiment, Data and Empirical strategy

The Sri Lanka Microenterprise survey spans a representative sample of 408 microenterprises, with a capital stock of less than 100,000 LKR or ~$1000, in the industries of retail, sales and manufacturing. The firms have been observed for 9 waves each spanning 3 months and starting in April 2005. Between the first and second period and the third and fourth period, half of the firms were given a cash or in-kind grant (both equipment and inventories) 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. The LKR 20,000 grants correspond to around 6 months of median profits and around 110% of the median capital stock in the base period. Relevant for the issue of technological upgrading, even the cash grants were used to purchase new materials or equipment, suggesting that owners expected positive returns to these items. On average 43% and 18% of the 10,000 LKR cash grant and 34% and 16% of the 20,000 LKR cash grant were spent on the purchase of inventories and equipment respectively.

Importantly the survey includes the necessary variables of static (labour, energy expenditures and materials) and dynamic (capital) inputs that allow the estimation of production functions in the revenue form.

For a more detailed discussion of the experimental design and description of the data I refer the reader to the original paper.

3.1 Empirical strategy

The general empirical approach for estimating the treatment effect on TFP follows a two-step procedure that is commonly used in a variety of contexts to estimate the determinants of TFP (Coe and Helpman, 1995; Bernard and Jensen, 1999; Fernandes and Isgut, 2005). In the first step, a production function is estimated to predict the TFP residual, which is then regressed in the second stage in a standard treatment effects estimation. Since an unbiased TFP residual (and thus an unbiased estimation of treatment effects) depends crucially on a consistent estimation of the production function in the first stage, this requires as much attention as the subsequent estimation of treatment effects. The following discussion will give a brief outline of the standard approaches and issues arising with production function estimation especially in the context of this study but omits any general detail, which can be found in more thorough discussions such as Van Beveren (2007) and Eberhardt and Helmers (2010).

3.1.1 Production functions

Consider a standard log-linearized Cobb-Douglas production function with Hicks-neutral technology that we want to estimate:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_0 + \eta_i + \gamma_t + \omega_{it} + \upsilon_{it} \tag{8}$$

where total factor productivity consists of the following components:

- β_0 captures average productivity across firms in the base period
- η_i is a time invariant firm specific productivity term which captures e.g. managerial talent
- γ_t is a period specific shock, common to all firms, e.g. a macroeconomic shock
- ω_{it} is the time variant, firm specific shock as discussed in section 2
- υ_{it} is a firm specific measurement error which is assumed to be serially uncorrelated.

The main source of bias in this specification is the effect of firm-specific productivity shocks ω_{it} on input choices, which is conventionally referred to as transmission bias (Eberhardt and Helmers, 2010). Additionally input use will be determined by the firm-specific fixed productivity term η_i. Estimating this equation using OLS, the coefficients on static inputs are generally assumed to be upwards biased, while the capital coefficient is downwards biased (Van Beveren, 2007). Applying a within-transformation can eliminate bias due to the time-invariant firm specific productivity level η_i, but the remaining correlation between the demeaned inputs and the current demeaned productivity shock $\ddot{\omega_{it}}$ often leads to strong downwards Nickell-bias (Nickell, 1981).

The two most common approaches to overcome these issues are the estimation of above function - or a transformation of it - in a dynamic panel framework, or to exploit the structural implications of a model such as in Section 2 and introduce a control function.

Dynamic panel methods If we are willing to make the assumptions that the firm specific productivity shock ω_{it} follows an AR1 process of the form:

$$\omega_{it} = \rho\omega_{i,t-1} + \xi_{it}, \text{ where } |\rho| < 1, \ \xi_{it} \sim MA(0) \tag{9}$$

we can obtain a dynamic autoregressive distributed lag model by expressing $\omega_{i,t-1}$ using Eq. (8) and using this and Eq. (9) to rewrite Eq. (8) to obtain

$$y_{it} = \rho_1 y_{i,t-1} + \beta_k k_{it} - \rho\beta_k k_{i,t-1} + \beta_l l_{it} - \rho\beta_l l_{i,t-1} + \beta_m m_{it} - \rho\beta_m m_{i,t-1} + a_i + \tau_t + e_{it} \tag{10}$$

where $e_{it} = \xi_{it} + (\upsilon_{it} - \rho\upsilon_{it-1})$, $a_{it} = (1-\rho)(\beta_0 + \eta_i)$ and $\tau_t = (\gamma_t - \rho\gamma_{t-1})$. The coefficients on the lagged inputs are now combinations of the coefficient on the lagged dependent variable and the respective contemporaneous inputs. This common factor restriction may not hold and will be tested in the empirical section.

This transformation eliminates the autoregressive part of the error term ω_{it} and leaves only the productivity innovation ξ_{it}. In the context of section 2 this would include the productivity innovation both through investment and the purchase of intermediate inputs in each period. The above specification can then be estimated in a GMM framework with suitable lags of the variables in levels for the equation in differences (Arellano and Bond, 1991) and lags of differences for the variables in levels (Blundell and Bond, 1998). The inclusion of the specification in levels is important, since high persistence in the time series in the sample leads to severe downwards bias in the equation in differences (Griliches and Mairesse, 1995). Following the discussion in section 2, I treat all inputs as endogenous (in contrast to other studies, which treat capital as predetermined) and use the according moment conditions in the estimation in section 4.

Structural estimators A second strategy is the usage of a class of estimators first introduced by Olley and Pakes (1996) and subsequently and substantially enhanced by Levinsohn and Petrin (2003), Ackerberg, Caves, and Frazer (2006) and Wooldridge (2009). The strategy essentially amounts to introducing a term g(.) into Eq. (8), which is most commonly a lagged polynomial of a flexible input and capital. Since a flexible input responds freely to the current productivity shock and capital level it can be used as a proxy for the former. Keniston (2011) shows that the use of materials as a flexible input variable is appropriate in the context of the SLMS data. We obtain:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + g(k_{it-1}, m_{it-1}) + \xi_{it} + \gamma_t + \upsilon_{it} \tag{11}$$

If g(.) successfully proxies for last period's productivity shock, this leaves only the productivity innovation ξ_{it}, the common time-specific shock, and the measurement error in the compound error term. Wooldridge (2009) then suggests using appropriate moment conditions as in the dynamic panel methods and estimating the above equation in a GMM context.

3.1.2 Estimation of treatment effects

To estimate the treatment effect I follow the same approach as DMW and regress the predicted TFP levels on the treatment dummies in both a OLS and FE regression using their preferred sample. The general specification is of the following form:

$$TFP_{it} = \alpha + \sum_{g=1}^{4} \beta_g \mathrm{T}_{git} + \textstyle\sum_{g=1}^{4} \delta_s \mathrm{T}_{git} {*} X_{sit} + \displaystyle\sum_{t=2}^{9} \gamma_t + \sum_{t=2}^{9} X_{sit}\gamma_t + \eta_i + \omega_{it} + \upsilon_{it} \tag{12}$$

In this specification $g = 1, .., 4$ indicates the four different treatment types (small and large in-kind and cash grants), γ_t are wave fixed effects, η_i are firm specific fixed effects in the FE specification and ω_{it} and υ_{it} are unobserved firm specific productivity shocks and measurement error as in section (2). Interaction terms with demeaned X_{sit} are added that were hypothesised to affect the ability of firms to absorb the technology embodied in capital goods. Since time trajectories may differ for firms with different characteristics, an interaction term between these variables and the time fixed effect is included in all models. I only report FE estimates and comment on any deviations from these in the OLS estimates. The estimates are the intent-to-treat effect but since there was virtually no non-compliance with the treatment, it effectively coincides with the average treatment effect.

Since the treatment is randomised, identifying causality is not an issue here. However TFP, the variable of interest is the result of the estimation of production functions. Therefore characteristics of the different procedures employed may potentially bias the subsequent treatment effect estimation.

First, bias in the production functions will lead to bias in the treatment effect estimation. The predicted TFP level is the part of output that is not explained by the inputs.

If the input coefficients are underestimated, the predicted residual will contain some uncaptured effect of the inputs. In this case what the treatment dummies pick up may be the effect of the inputs that have been not been controlled for in the first stage and not an actual productivity increase. On the other hand, if the input coefficients suffer from an upwards bias due to correlation with unobserved productivity, the predicted TFP values will be an underestimate of the true level. This will make it more difficult to identify treatment effects on productivity when they in fact exist.[7] Since we do not know what the true coefficient is, the best way to address this problem is to see whether the treatment effects change significantly depending on whether a TFP residual is used from an estimator that traditionally leads to upwards or downwards bias.

There are further concerns over whether some of the above estimators will produce a residual TFP that is suitable for this purpose. Consider first the dynamic panel methods. The motivation for using a lagged dependent variable was to reduce the problem of autocorrelation in the error term. However, this creates another problem when estimating the effect of the treatment on productivity.

Independent of the estimation, if there was an embodied technology mechanism present we would expect the treatment to raise productivity in the period in which the capital stock is increased, that is at the time of treatment for those firms receiving an equipment grant, and perhaps in later periods for those who receive the cash grant. Focusing on the former for simplicity, this would mean that from the pre-treatment to the treatment period there is a one-time increase of ω_{it} which then remains at a constant higher level relative to the control firms. In the notation used above, this jump is captured by the the innovation term ξ_{it}. In the periods following the treatment, the technology effect of the treatment will partly be captured by the lagged dependent and explanatory variables, even if the treatment dummy is still switched on. However since lags of output and the inputs do not physically produce current output, they rather capture a continuity in productivity. This leaves significantly less variation in productivity shocks relative to the control group left to explain by the treatment dummy. In the context of the WLP routine, this is equally a concern, as the lagged polynomial will partially control for the productivity that is potentially introduced through the treatment.

Another issue arising in the context of GMM is a loss of the initial periods. Since we use a lagged difference of the explanatory and dependent variable, we loose two initial observation. The first round of the treatment however was between period 1 and 2. That is, we would expect the technology shift to be measurable in ξ_{i2}. In period 3 however,

[7] In a recent study on the effect of business training on profits Karlan and Valdivia (2011) find positive effects on the residual from a production function estimated by OLS. Depending on the bias on the coefficients this could either underestimate the true effect, or on the other hand capture an increase in sales due to an increase in capital.

depending on the size of ρ the productivity increase through the treatment will be captured largely by the lagged dependent and explanatory variables.

The problem of over-controlling in GMM is a common problem. Eberhardt and Helmers (2010) in their investigation of the determinants of technology levels do not use the residuals obtained from GMM. This issue could be addressed by using a static production function as in Teal and Baptist (2008), who follow a similar procedure to estimate the determinants of firm level productivity. However, the dynamic specification has been introduced in the first place to address the issue of serial correlation in the error. It is thus a compromise between having a dynamically complete model and the ability to identify the treatment effect.

Another solution is to estimate the production functions and then use the coefficients from the model that in theory has the least bias and use these to manually subtract the effects of the current inputs (which are physically producing current output). This is consistent with the definition of the TFP residual and solves both the problem of loosing initial periods as well as the fact that lags of the explanatory variables and the productivity proxy may capture more of TFP than we would like.

4 Treatment effects on productivity

4.1 Production functions

The first part of the empirical section presents results of estimating several standard production functions that cover the main specifications suggested in the literature. All are based on the basic production function in Eq. (8) and presented in Table 1.

Columns (1) and (2) in Table 1 show the results for OLS and FE estimation. The coefficients appear biased in the directions that are commonly found in the literature (Van Beveren, 2007) and provide upper and lower bounds between which the true coefficients should generally lie.

[Table 1 here]

Columns (3) and (4) implement the structural estimator in a GMM framework as introduced by Wooldridge (2009) and used in Petrin and Levinsohn (2012) both in a static and a dynamic specification. Rows 4-12 together contain the polynomial that proxies for the productivity shock in the previous period. The reported tests for first and second order serial correlation (AR1 and AR2 respectively) indicate that only the dynamic specification is dynamically complete. This is suggested by the result that the hypothesis of no first order serial correlation is rejected but the hypothesis of no second order serial correlation is not rejected.

The remaining columns implement the Difference and System GMM estimators both in static and dynamic version through the inclusion of a lagged dependent variable. The most acceptable specifications here are columns (8) and (9). The serial correlation tests indicate dynamically complete models, the Hansen test fails to reject the exogeneity of the instruments and the models display realistic returns to scale. In all specifications a stepwise reduction of the lag length was implemented to investigate whether the models may suffer from instrument proliferation, with satisfying results (not reported).

4.2 Treatment effects

4.2.1 Basic treatment effects and heterogeneity

[Tables 2-6 here]

Recall that the main issue with identifying the treatment effects is that this relies on consistently estimating the production functions, but estimating the production function consistently makes it more difficult to estimate the treatment effect. From this perspective I will employ several TFP estimates. OLS, as it leads to upwards biased coefficients, should serve as a conservative benchmark. The static BB specification in column (6) produced both realistic coefficients and does not suffer from strong serial correlation, so it should be relatively unbiased. The extended dynamic BB specification in column (9) is most appropriate from a theoretical perspective but contains many lagged elements that capture some of the firm's productivity level. I therefore use it to manually predict TFP levels using only the contemporaneous inputs.[8] The TFP predicted from the WLP specification is also included for comparison. Since there obviously is no way to assess the specific bias in each specification and there will necessarily be some variation between the TFP estimates using several of them should increase confidence in the results.

Tables 2-6 report the results of estimating (12) using different TFP estimates from the production functions in Table 1 as the dependent variable. Overall, it appears that there were no significant increases through the treatments on average but only in subgroups of the population. The results from Table 2 shows a marginally significant result for the large in-kind grant in combination with higher than average educational attainment. However, this is not consistent across TFP estimates from different production functions. Table 4 finds a robust increase in TFP through the large in-kind grant across all TFP residuals. Table 6 shows that TFP increased in firms with higher risk aversion mostly among the large in-kind recipients but this is not strongly significant across the different TFP residuals. However this finding is in accordance with the theoretical model in DMW, who suggest that

[8]Since the labour coefficient in this specification is particularly low, I also calculate TFP by manually changing the labour coefficient to 0.15 and 0.25 but this does not affect the results.

risk averse owners have higher unrealised returns to capital. The unexpected equipment grant may have helped these owners to invest in new technology that may have otherwise appeared too risky to implement. The age of the business and the gender of it's owner on the other hand appear to play no role in adopting new technology through the intervention.

[Table 7 here]

Table 7 presents the results from a different specification that takes into account the hypothesis that firms that are far below the available technology level will be able to catch up rapidly. I estimate the effect of the individual treatments on TFP by FE but split the sample into quartiles of TFP in the initial period. There is a strong degree of mean reversal present in the quartile trajectories but this should be sufficiently captured by the included quartile-specific time dummies. The dependent variable is the TFP measure that is manually predicted from the extended dynamic BB specification in column (9) in Table 1. From the results it appears that the most unproductive and the most productive firms were able to increase their TFP through the treatment. However, the results in the highest quartile are not stable across different TFP estimates. Taking the coefficients at face values suggests that the large in-kind treatment allowed firms from the lowest initial TFP quartile to increase their output by 42% at any given input usage.

Columns (5-8) replace TFP with real profits as the dependent variable. This is an analogous specification to the one used to produce Table II in De Mel, McKenzie, and Woodruff (2008) (which estimates the treatment effects on profits) but again, split into TFP quartiles. Here it appears that the pattern of treatment effects for profits quite closely coincide with the pattern of productivity increases. The heterogeneity of treatment responses with respect to initial productivity appears relevant.

4.2.2 IV estimates

The above results cannot tell us which channel was responsible for the TFP increase. Therefore Table 8 uses a more direct way of assessing the treatment effect in the different productivity quartiles. In these tables the dependent variable is regressed on the explanatory variable of interest which is in turn instrumented by the four treatment dummies. Ideally one would include all three inputs into the specification but it appears that the instruments are not sufficiently strong to identify all inputs individually. Therefore it cannot be said with certainty that the captured effects are indeed those of the instrumented variable alone or some factors that are covariate with both the treatment and the endogenous explanatory variable. However they give some indication of what the relevant (observable) channel was. Also note that the coefficients may not capture the ATE since only some firms increased their capital stock in response to the treatment and these firms may not have the same productivity response to capital increases as the average firm. The coefficients should thus be regarded as the Local Average Treatment Effect. Also note that the inputs are only weakly identified, so the coefficients may have substantial finite sample bias. They still indicate however, what the relevant channels were.

[Table 8 here]

Table 8 suggest that out of the three inputs, only capital had an impact on productivity levels.[9] The positive effect in the first quartile is consistent across TFP measures used, while the negative effect jumps between the third and fourth quartile depending on the TFP measure. There seems to be no productivity effect through increased materials used or more hours worked. This suggests that an inability to purchase materials is not a constraint to firm productivity. Also, perhaps noteworthy is that while the large treatments resulted in an increase in hours worked, there was no reduction in productivity. This tentatively suggests that the hypothesis that informal firms face managerial constraints in larger operations may not hold in this sample.

5 Microenterprise productivity in perspective

The above results suggest that a subsample of firms indeed experienced increases in productivity through the intervention. However, a more complete understanding of the magnitude of these effects requires a reference point of productivity levels in the wider economy. To provide this and thus to develop an understanding of the potential gap that microenterprises have to bridge, I use data from the World Bank Enterprise Surveys that collect firm data in a large number of countries around the world. The dataset contains a representative survey of formal Sri Lankan firms in 2010, including all variables required for the estimation of production functions. This allows the comparison of the SLMS firms to their formal counterparts in terms of input use and productivity. The methodology of this exercise is in principle similar to Teal and Baptist (2008) who compare productivity levels between formal Ghanaian and South Korean manufacturing firms and Saliola and Seker (2011) who do the same for formal manufacturing firms across many developing countries, also using the World Bank Enterprise Surveys. Compared to these studies the harmonisation of separate datasets is less complex as there is no need to make variables comparable across countries. To proceed, I deflate all monetary values and make measures of inputs

[9]This result in fact rejects the theoretical assumptions made by the structural estimators.

comparable.[10] The last available SLMS data collection lies in 2008, while the Enterprise Surveys were conducted in 2010. I include a time trend in the estimation of production functions but the assumption that TFP grows linearly over time may very well be restrictive. GDP growth dipped below a linear trend in the financial crisis in 2009 and did not recover until 2010 and much of this effect is likely to come through a reduction in factor usage. The remaining discrepancy suggests that estimated TFP levels for the ES firms are likely to lie a few percentage points below their actual value. However this discrepancy should be sufficiently small compared to the differences between sectors to be negligible.[11] A further issue arises through the fact that the Enterprise Surveys are only cross-sectional, which allows estimation only by OLS.

First I present summary statistics for the individual sectors. These give relevant insights into the characteristics and history of formal firms in the sample.

[Table 9 here]

Most notable here is that while many enterprises have started as formal businesses there is also a considerable number of firms that have their beginnings in the informal sector. This is inconsistent with a view of the informal sector as both separate and stagnating. It supports the view that the most productive firms can eventually make the transition into the formal sector when the advantages of formalisation outweigh the costs of taxation and regulation. Also, those firms that have begun unregistered spent a considerable amount of time as an informal firm before registering. It may thus very well be that some of the firms captured in the SLMS survey will at some point make the transition into the formal sector.

Now, I turn to productivity differences between firm categories. Table 10 estimates differences in average TFP levels for different categories of firms. Columns (1) and (2) estimate TFP of the ES firms relative to the microenterprises. The results suggest that only large firms have a significantly different TFP level. A given amount of capital and labour in large firms results in 55% more revenues than in the microenterprises. Note that the size of the coefficients and their significance vary with the restriction of waves used for comparison. Having a higher number of observations clearly results in smaller standard errors. However, using the wave in the SLMS survey that is closest in time to the ES may improve comparability.

[10] Labour is measured in hours per week in the SLMS data, while it is measured as current employees in the Enterprise Surveys. I therefore use the legal Sri Lanka work week of 38.5 hours to approximate hours worked in the firms. Since these are registered firms, legal regulations should be close the true values.

[11] I have also attempted to estimate TFP levels at the national level and correct for these trends but the estimation delivers no sensible results (labour has a large and negative coefficient).

Since a subsample (24%) of microenterprises are registered in the initial period columns (3) and (4) estimate the difference in TFP between informal and formal firms in the SLMS sample. The results suggest that there is no discernible difference between these two categories of firms. This is consistent with a model of formalisation choices by Gelb et al. (2009). The authors predict that in countries incentives for formalisation are low when it is associated with costs but does not substantially increase access to public goods and services. In this case informal and formal firms will co-exist with overlapping productivity levels. De Mel, McKenzie, and Woodruff (2012b) suggest that demand for formalisation is not very high in Sri Lanka and thus a pattern as described above is not unlikely.

Columns (5) and (6) show differences in TFP relative to the untreated sample. This finding provides an explanation for the rejection of differences in TFP levels for SMLS and small and medium sized ES firms in columns (1) and (2). It appears that the treatment allowed informal firms to approach the productivity levels of their formal counterparts, while the untreated firms remain lagging behind.

Columns (7) and (8) split the sample along initial TFP levels in the SLMS firms. The results suggest that while the least productive microenterprises are clearly less productive than the average small and medium formal firm, the more productive microenterprises overlap with their SME counterparts. Note here that the wave restriction has a significant impact on the results. This is most likely due to the fact that there is a degree of mean reversal present in the TFP levels. The initial split in TFP in the informal firms is less pronounced in the later periods and differences thus not statistically significant anymore.

Recall the treatment effects in table 7, which showed that the large in-kind treatment increased TFP by 0.42 in the least productive quartile. Table 10 puts these results into perspective. It suggests that the large in-kind treatment resulted in increases in TFP that bring the least productive microenterprises on par with their most productive counterparts of equal size and the average small and medium sized ES firm. It also suggests a reason why the SLMS firms starting with average productivity saw no significant increases. These firms are already similar in their productivity levels to small and medium firms in the formal sector.

[Table 10 here]

6 Interpretation

Several patterns emerge from the reported results. First, it is striking that only a subsample of owners which received a capital grant that represents up to 6 months worth of median profits and a doubling of the median capital stock were able to increase their productivity (and for whom these treatment effects are strongly significant across all TFP estimates). Under credit constraints, this would mean that owners have to forsake consumption for a significant amount of time to accumulate sufficient liquidity to purchase more productive equipment. It is also consistent with a scenario in which technology does not increase gradually. In their conclusion DMW are puzzled why firms do not grow incrementally when returns to capital are so high. The evidence above provides at least a partial explanation. Relevant to microfinance, the evidence suggests that only relatively large loans have the potential to increase productivity in microenterprises. The fact that the cash grants had no strongly significant effects on productivity also supports an argument made by Fafchamps et al. (2011b) who suggest that giving in-kind grants may be important for individuals with self-commitment problems.

The observation that there is strong overlap between the group of firms that experience returns to capital and those that increase their productivity suggests the measured treatment effects found by DMW have an important technology component. This observation is also a relevant explanation both for the fact that firm owners do not decapitalise the in-kind grant at the next opportunity and for the finding that after several years de Mel, McKenzie, and Woodruff (2012) still find increased profits in the treatment group. As suggested in the theoretical section a TFP increase will permanently move the steady state capital and profit level outwards.

The results show that the average firm was only able to increase its TFP level if it started in the lowest TFP quartile.[12] This is consistent with the assumption made that it is more feasible for low-productivity firms to catch-up to an externally determined productivity level (for example by moving from a traditional production method to the utilisation of more modern machinery). The comparison of TFP levels with those from the ES firms suggests that this productivity level is similar to that of formal SMEs. However it may be that these do not have very high levels of productivity themselves. The important step in TFP in Sri Lanka lies between SMEs and large formal enterprises, which produce substantially more output with their given inputs. Overall however the findings of this paper lead to a rather optimistic picture of the role of microenterprises and the informal sector. Microenterprises are not substantially behind SME productivity levels. A non-negligible share of formal firms had their roots in the informal sector. The relaxation of liquidity constraints through capital grants (if large ones) can help the most unproductive firms to catch up with the rest. This may not only have important implications for the owners of these firms but for the structure and productivity of the informal sector as a whole.

[12] For the highest productivity quartile the results from different TFP estimates are too unstable to be taken as reliable evidence for TFP shifts.

7 Conclusion

This paper uses experimental data to estimate two interrelated questions. First, do cash and in-kind grants only lead to an increase in capital stock and thus increased profits, or does it allow firms to increase their level of technology? Second, will this increase be enough to reduce the productivity gap between microenterprises and formal SMEs? I find that most significantly a large in-kind grant positively affects productivity levels, and only in firms with owners of above-mean cognitive ability and risk aversion. A TFP increase is also strongly significant in the subsample of firms that show the lowest productivity levels in the initial period. For firms that experience an increase in productivity the effect is economically significant. The large in-kind grant in the lowest productivity quartile results in a 42% increase in revenues at any given level of inputs. There is also some indication that the returns to capital estimated in the study that produced the dataset used coincide with the above productivity increases. This suggests that returns to capital for microenterprises contain a significant return to increased productivity.

Estimating TFP levels in formal small, medium and large enterprises gives a perspective for these TFP increases. Overall, control firms are around 20% less productive than SMEs and around 70% less productive than large firms. Separating the microenterprises into initial productivity quartiles shows that the more productive microenterprises have similar TFP levels as the average SME. The treatment effect through large in-kind grants helps the least productive firms to increase their TFP to the same level, showing that capital grants can generate convergence in productivity between microenterprises and SMEs, while a gap to large enterprises remains.

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Table 1: Production functions

			WLP		Static GMM		Dynamic GMM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	FE	Static	Dynamic	AB	BB	AB	BB	BB
lnK	0.11***	0.14***	0.15***	0.15***	0.023	0.17**	0.087	0.14*	0.15***
	(0.02)	(0.03)	(0.04)	(0.05)	(0.07)	(0.08)	(0.12)	(0.07)	(0.05)
lnL	0.21***	0.099***	0.095	0.042	-0.12	0.18*	-0.045	0.095**	0.075
	(0.03)	(0.03)	(0.12)	(0.09)	(0.11)	(0.10)	(0.05)	(0.04)	(0.10)
lnM	0.62***	0.37***	0.46***	0.39***	0.44***	0.68***	0.33***	0.49***	0.44***
	(0.02)	(0.02)	(0.08)	(0.10)	(0.08)	(0.06)	(0.04)	(0.05)	(0.05)
lag lnK			-0.37	-0.28					-0.057
			(0.86)	(0.64)					(0.04)
lag lnM			-0.57	-0.52					-0.087*
			(0.52)	(0.37)					(0.05)
lag lnK*lnM			0.058	0.11					
			(0.11)	(0.10)					
lag lnK2			0.013	-0.033					
			(0.10)	(0.08)					
lag lnM2			0.052	-0.0067					
			(0.04)	(0.04)					
lag lnK2*lnM			-0.0025	-0.0067					
			(0.01)	(0.01)					
lag lnK*lnM2			-0.0028	0.00096					
			(0.00)	(0.00)					
lag lnK3			0.00068	0.0032					
			(0.00)	(0.00)					
lag lnM3			0.00047	0.000024					
			(0.00)	(0.00)					
lag lnY				0.51***			0.16***	0.30***	0.43***
				(0.12)			(0.04)	(0.06)	(0.06)
lag L									0.030
									(0.05)
Constant	1.52***	3.87***	4.96*	2.76		0.61		0.43	0.85**
	(0.18)	(0.29)	(2.92)	(2.18)		(0.74)		(0.66)	(0.38)
N	3036	3036	2590	2582	2512	3036	2143	2629	2512
Hansen			0.83	0.30	0.74	0.65	0.16	0.33	0.43
AR1			4.1e-10	0.00000035	2.7e-11	2.9e-11	3.0e-10	2.1e-10	5.4e-10
AR2			0.0033	0.67	0.0041	0.19	0.11	0.70	0.79
Instr			47	61	74	80	105	104	118
CRS	0.94	0.61	0.70	1.20	0.33	1.03	0.44	1.03	0.96
CRS_pvalue	0.054	1.4e-22	0.0027		0.00000032	0.76			

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: Dependent variable is the log of real revenues. Estimators employed are are OLS, FE - firm fixed Effects, WLP - Wooldridge (2009) implementation of Levinsohn and Petrin (2003), AB - Arellano and Bond (1991) 'Difference' GMM, BB Blundell and Bond (1998) 'System' GMM. AB and BB use the 2-step estimator using the Windmeijer (2005) correction. OLS and FE errors are clustered at the firm level. All use the sample favoured by DMW. The p-value of the test for constant returns to scale can not be provided for all specifications as the sum of coefficients has to be calculated manually.

Table 2: Treatment effects with education heterogeneity tests

	(1) OLS	(2) Static WLP	(3) Static BB	(4) Dynamic BB
Cash 1k	0.095	0.016	0.076	0.12
	(0.08)	(0.11)	(0.08)	(0.08)
Cash 2k	-0.040	-0.094	-0.094	0.018
	(0.10)	(0.12)	(0.10)	(0.10)
In-kind 1k	-0.044	-0.17*	-0.078	-0.0080
	(0.07)	(0.09)	(0.08)	(0.07)
In-kind 2k	0.099	-0.14	0.041	0.15
	(0.11)	(0.10)	(0.11)	(0.10)
C1*Education	-0.0079	0.024	-0.0030	-0.016
	(0.04)	(0.06)	(0.04)	(0.03)
C2*Education	-0.0017	0.00028	0.0014	-0.0096
	(0.02)	(0.04)	(0.02)	(0.02)
I1*Education	0.049*	0.012	0.048*	0.059**
	(0.03)	(0.03)	(0.03)	(0.02)
I2*Education	0.020	-0.0051	0.024	0.019
	(0.03)	(0.02)	(0.04)	(0.03)
Constant	-0.0080	0.021	-0.0090	2.48***
	(0.04)	(0.04)	(0.04)	(0.04)
R2	0.0041	0.0095	0.0042	0.051
N	3036	2590	3036	3036

Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: Dependent variables are the TFP residuals from the respective production functions as indicated in the column title. All models contain firm and time dummies and interactions of time dummies and the interaction variable. Estimation by FE. The interaction variables have been demeaned. All errors are clustered at the firm level. All use the preferred sample of DMW.

Table 3: Treatment effects with age of business heterogeneity tests

	(1) OLS	(2) Static WLP	(3) Static BB	(4) Dynamic BB
Cash 1k	0.100	0.018	0.081	0.12
	(0.08)	(0.09)	(0.08)	(0.08)
Cash 2k	-0.065	-0.18	-0.13	0.011
	(0.09)	(0.15)	(0.09)	(0.10)
In-kind 1k	-0.032	-0.17*	-0.066	0.0057
	(0.08)	(0.09)	(0.08)	(0.07)
In-kind 2k	0.16	-0.12	0.10	0.19*
	(0.11)	(0.08)	(0.12)	(0.11)
C1*Age businesss	-0.0042	0.0075	-0.0045	-0.0033
	(0.01)	(0.01)	(0.01)	(0.01)
C2*Age businesss	-0.0091	-0.019	-0.012	-0.0055
	(0.01)	(0.02)	(0.01)	(0.01)
I1*Age businesss	-0.0028	0.0030	-0.0031	-0.0036
	(0.01)	(0.01)	(0.01)	(0.01)
I2*Age businesss	0.020	0.0030	0.021	0.015
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.0037	0.032	-0.0050	2.48***
	(0.04)	(0.04)	(0.04)	(0.04)
R2	0.0044	0.011	0.0050	0.048
N	3021	2579	3021	3021

Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: Dependent variables are the TFP residuals from the respective production functions as indicated in the column title. All models contain firm and time dummies and interactions of time dummies and the interaction variable. Estimation by FE. The interaction variables have been demeaned. All errors are clustered at the firm level. All use the preferred sample of DMW.

Table 4: Treatment effects with ability heterogeneity tests

	(1) OLS	(2) Static WLP	(3) Static BB	(4) Dynamic BB
Cash 1k	0.11	0.011	0.088	0.13
	(0.09)	(0.09)	(0.09)	(0.08)
Cash 2k	-0.063	-0.17	-0.12	0.0074
	(0.09)	(0.12)	(0.09)	(0.09)
In-kind 1k	-0.024	-0.18**	-0.060	0.013
	(0.08)	(0.09)	(0.08)	(0.07)
In-kind 2k	0.11	-0.090	0.052	0.16*
	(0.10)	(0.08)	(0.10)	(0.09)
C1*Ability	-0.041	0.093	-0.043	-0.039
	(0.07)	(0.09)	(0.08)	(0.07)
C2*Ability	0.038	0.10	0.049	0.0077
	(0.06)	(0.10)	(0.06)	(0.06)
I1*Ability	0.12	-0.11	0.12	0.11
	(0.08)	(0.10)	(0.08)	(0.07)
I2*Ability	0.19**	0.18***	0.21**	0.18**
	(0.09)	(0.06)	(0.10)	(0.09)
Constant	-0.0049	0.035	-0.0056	2.48***
	(0.04)	(0.04)	(0.04)	(0.04)
R2	0.0082	0.015	0.0091	0.055
N	2960	2535	2960	2960

Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: Dependent variables are the TFP residuals from the respective production functions as indicated in the column title. All models contain firm and time dummies and interactions of time dummies and the interaction variable. Estimation by FE. The interaction variables have been demeaned. All errors are clustered at the firm level. All use the preferred sample of DMW.

Table 5: Treatment effects with gender heterogeneity tests

	(1) OLS	(2) Static WLP	(3) Static BB	(4) Dynamic BB
Cash 1k	0.093	0.020	0.075	0.12
	(0.08)	(0.09)	(0.09)	(0.08)
Cash 2k	-0.062	-0.14	-0.12	0.0063
	(0.09)	(0.11)	(0.09)	(0.10)
In-kind 1k	-0.034	-0.17*	-0.068	0.0029
	(0.08)	(0.09)	(0.08)	(0.07)
In-kind 2k	0.075	-0.18*	0.015	0.11
	(0.12)	(0.10)	(0.12)	(0.11)
C1*Female	-0.015	-0.16	0.0046	-0.077
	(0.16)	(0.18)	(0.16)	(0.16)
C2*Female	-0.15	-0.38*	-0.16	-0.13
	(0.18)	(0.21)	(0.17)	(0.19)
I1*Female	-0.11	-0.15	-0.11	-0.11
	(0.15)	(0.17)	(0.15)	(0.14)
I2*Female	-0.12	-0.31	-0.13	-0.18
	(0.23)	(0.20)	(0.25)	(0.23)
Constant	-0.0083	0.022	-0.0093	2.48***
	(0.04)	(0.04)	(0.04)	(0.04)
R2	0.0030	0.013	0.0033	0.049
N	3036	2590	3036	3036

Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: Dependent variables are the TFP residuals from the respective production functions as indicated in the column title. All models contain firm and time dummies and interactions of time dummies and the interaction variable. Estimation by FE. The interaction variables have been demeaned. All errors are clustered at the firm level. All use the preferred sample of DMW.

Table 6: Treatment effects with risk aversion heterogeneity tests

	(1) OLS	(2) Static WLP	(3) Static BB	(4) Dynamic BB
Cash 1k	0.11	0.049	0.089	0.13*
	(0.08)	(0.09)	(0.08)	(0.08)
Cash 2k	-0.046	-0.090	-0.097	0.013
	(0.09)	(0.12)	(0.09)	(0.09)
In-kind 1k	-0.038	-0.16*	-0.073	0.00064
	(0.08)	(0.09)	(0.08)	(0.07)
In-kind 2k	0.038	-0.17*	-0.025	0.090
	(0.11)	(0.09)	(0.12)	(0.10)
C1*CRRA	0.071*	0.092*	0.074*	0.074*
	(0.04)	(0.05)	(0.04)	(0.04)
C2*CRRA	0.024	-0.022	0.0070	0.045
	(0.05)	(0.09)	(0.05)	(0.05)
I1*CRRA	-0.020	-0.088*	-0.030	0.0041
	(0.04)	(0.05)	(0.04)	(0.04)
I2*CRRA	0.12**	0.081*	0.13**	0.11*
	(0.06)	(0.04)	(0.06)	(0.06)
Constant	-0.0087	0.016	-0.0096	2.48***
	(0.04)	(0.04)	(0.04)	(0.04)
R2	0.0063	0.013	0.0068	0.052
N	3036	2590	3036	3036

Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: Dependent variables are the TFP residuals from the respective production functions as indicated in the column title. All models contain firm and time dummies and interactions of time dummies and the interaction variable. Estimation by FE. The interaction variables have been demeaned. All errors are clustered at the firm level. All use the preferred sample of DMW.

Table 7: Treatment effects on TFP and real profits by initial productivity quartile as indicated in the column title

	TFP				Profits			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Cash 1k	0.27	-0.054	-0.034	0.28***	0.22	0.079	-0.13	0.43***
	(0.21)	(0.14)	(0.09)	(0.10)	(0.21)	(0.15)	(0.14)	(0.14)
Cash 2k	0.23	0.053	-0.18	-0.021	0.89***	0.15	-0.030	-0.0032
	(0.18)	(0.10)	(0.17)	(0.14)	(0.19)	(0.14)	(0.22)	(0.21)
In-kind 1k	0.022	-0.033	-0.058	-0.034	0.30	-0.11	-0.026	0.21
	(0.16)	(0.11)	(0.11)	(0.12)	(0.20)	(0.13)	(0.20)	(0.15)
In-kind 2k	0.42***	0.12	-0.22*	0.24*	0.48***	0.029	-0.16	0.67
	(0.16)	(0.15)	(0.12)	(0.13)	(0.12)	(0.21)	(0.18)	(0.43)
Constant	1.51***	2.27***	2.75***	3.41***	7.32***	7.75***	8.06***	8.51***
	(0.07)	(0.05)	(0.04)	(0.05)	(0.08)	(0.07)	(0.07)	(0.07)
Observations	727	757	757	731	780	803	802	790
R^2	0.31	0.14	0.02	0.12	0.15	0.11	0.08	0.09

Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Note: All models contain time fixed effects and firm fixed effects. All standard errors are clustered at the firm level. All use the preferred sample of DMW.

Table 8: IV estimates of embodied technology increase

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
lnK	0.29**	-0.058	-0.22**	0.15
	(0.13)	(0.18)	(0.10)	(0.13)
Observations	727	757	757	728
UnderID	0.00021	0.0033	0.014	0.035
WeakID	11.3	5.73	4.53	3.68
Hansen	0.55	0.75	0.96	0.089

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
lnL	0.34	-0.16	0.46	0.52
	(0.56)	(0.44)	(0.52)	(0.39)
Observations	727	757	757	728
UnderID	0.13	0.13	0.56	0.29
WeakID	2.11	2.11	0.78	1.44
Hansen	0.090	0.81	0.39	0.19

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
lnM	0.17	0.22	-0.65	0.22
	(0.12)	(0.22)	(0.46)	(0.19)
Observations	727	757	757	728
UnderID	0.017	0.25	0.47	0.31
WeakID	4.54	1.53	0.97	1.81
Hansen	0.16	0.88	0.96	0.10

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Note: Dependent variable is the TFP predicted from the extended dynamic BB specification. The increase in capital, material, labour is instrumented by the treatment dummies. All models contain time and firm-specific fixed effects. All standard errors are clustered at the firm level. All use the preferred sample of DMW.

Table 9: Summary statistics of informal and formal enterprises at different size categories

		Obs	Mean	Std. Dev.	Min	Max
Hired employees	Micro (SLMS)	365	0.69	0.83	0	4
	Small (ES)	288	14.88	55.35	5	900
	Medium (ES)	232	64.00	127.91	5	1000
	Large (ES)	90	431.72	718.50	5	6100
Capital stock (thousand SLR)	Micro (SLMS)	327	46	52	0	405
	Small (ES)	143	2857	5919	5	40161
	Medium (ES)	101	19227	85964	7	854850
	Large (ES)	38	78118	192382	12	1147452
Start of business	Small (ES)	279	1990	17	1905	2010
	Medium (ES)	225	1987	21	1849	2011
	Large (ES)	88	1978	25	1861	2010
Employees at start	Small (ES)	268	9.75	30.74	1	350
	Medium (ES)	201	29.93	94.78	1	1200
	Large (ES)	77	133.21	277.41	1	1500
Registered at start	Small (ES)	281	0.70	0.46	0	1
	Medium (ES)	217	0.83	0.38	0	1
	Large (ES)	88	0.86	0.35	0	1
Time unregistered	Small (ES)	74	8.8	13.44	0	66
	Medium (ES)	33	7.4	12.35	0	52
	Large (ES)	9	13.2	13.66	2	40

Note: Firm data is from the Sri Lanka Microenterprise Survey (SLMS) and the World Bank Enterprise Surveys (ES)

Table 10: Average TFP levels for various categories of firm size and productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All waves	Waves > 7	All waves	Waves > 7	All waves	Waves > 7	All waves	Waves > 7
Small (ES)	0.12	0.33	0.14	0.34	0.21*	0.37	0.34***	0.63
	(0.11)	(0.46)	(0.11)	(0.46)	(0.12)	(0.46)	(0.12)	(0.45)
Medium (ES)	0.14	0.35	0.15	0.36	0.22*	0.38	0.35***	0.64
	(0.12)	(0.46)	(0.13)	(0.46)	(0.13)	(0.47)	(0.13)	(0.46)
Large (ES)	0.55***	0.75	0.56***	0.77	0.63***	0.79*	0.76***	1.05**
	(0.17)	(0.48)	(0.18)	(0.48)	(0.18)	(0.48)	(0.18)	(0.47)
Micro (SLMS): Formal			-0.017	-0.011				
			(0.05)	(0.06)				
Micro (SLMS): Treated					0.058	0.11*		
					(0.04)	(0.06)		
Micro (SLMS): TFP Quartile 2							0.15***	0.069
							(0.05)	(0.08)
Micro (SLMS): TFP Quartile 3							0.29***	0.11
							(0.05)	(0.08)
Micro (SLMS): TFP Quartile 4							0.42***	0.22***
							(0.06)	(0.08)
Reference: Micro	All	All	Informal	Informal	Untreated	Untreated	TFP Quartile 1	TFP Quartile 1
N	3301	901	3301	901	3301	901	3237	885
R2	0.0053	0.022	0.0055	0.022	0.0069	0.026	0.057	0.033

Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Note: Dependent variable is TFP in logs predicted from a OLS Cobb-Douglas production function. The reference category are micro firms covered in the study by DMW or a subsample thereof as indicated in the table footer. The equation contains a time trend. All standard errors are clustered at the firm level.