Experimental vs. Structural Estimates of the Return to Capital in Microenterprises*

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Abstract

This paper carries out the first comparison of production function parameters estimated by structural techniques with those estimated via randomized instrumental variables using a unique dataset and field experiment performed by De Mel, McKenzie, and Woodruff (2008b). In the context of a simple model of a household firm, I discuss the coefficients that each approach estimates, and the assumptions necessary to interpret those coefficients as the structural parameters of the model. I find that the values of structural and experimental estimators that most plausibly estimate the same parameters are indeed statistically and economically similar, suggesting that in some contexts structural models of production functions may be effective in recovering the parameters of production functions in the context of developing markets. These parameters may then be used to address questions relating to firm productivity and capital allocation that are both central to the study of firms in development, and potentially difficult to identify using randomized variation alone.

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Introduction

The estimation of production functions, in particular the measurement of the returns to capital, has a long history and a wide scope. Topics as diverse as the macroeconomic study of growth, the role of competition in driving productivity, and the effect of market imperfections on output all rely on a model of how firms transform inputs into outputs, and may depend critically on the parameters of that model. The importance of the issue, and the difficulties inherent in the estimation, have given rise to a substantial literature on structural estimation techniques, recently reviewed in Ackerberg, Benkard, Berry, and Pakes (2007). This paper contributes to this literature by comparing the production parameters estimated using these structural techniques with those derived from an instrumental variables regression of output on capital stock, with capital instrumented by random cash shocks to the firm. I make use of a unique dataset and randomized experiment carried out by De Mel, McKenzie, and Woodruff (2008b) (henceforth DMW) in which the authors implemented a program through which randomly chosen Sri Lankan microenterprises were given grants of various sizes (either in cash or physical capital or materials) and their subsequent production activities were carefully recorded over a two-year period. This data allows a comparison between structural estimators that may be applicable to a wide range of observational data (but depend upon stronger assumptions) and the results of randomized trials that is robust to a wide range of potential sources of bias.

The population of microenterprises in Sri Lanka is a highly specific one–De Mel, McKenzie and Woodruff surveyed only firms with less than about $1000 in capital (not including land or buildings)–and the success or failure of the structural estimators in this context does not imply they might not perform differently in another context, for example one in which markets are better developed but inputs are less flexible. Nevertheless, the parameters of production functions of microenterprises are of significant interest in their own right. The broad role of microenterprises in developing countries is the subject of a lively debate–one perspective argues that they may be high productivity firms held back by credit constraints or other frictions, while another view is that informal enterprises serve as a low-returns safety net for individuals excluded from the formal sector (Porta and Shleifer 2008). A broader knowledge of the production functions of microenterprises is clearly an important factor in this debate, and hence in informing policy towards the informal sector. Another source of interest in the returns to capital of microenterprises lies in its implications for the functioning of markets. As discussed in Banerjee and Duflo (2009), with perfectly functioning capital markets all firms should have the same risk-adjusted return to capital, which in turn should be equal to the interest rate. Estimating the extent and sectors in which this prediction does not hold true may then inform us of the extent of capital market imperfections in the broader economy.

Despite the broad concensus on the importance of understanding production functions, estimation has proved difficult for a variety of reasons. First, since unobserved shocks to productivity will affect both output and a firm's choice of inputs, a naive regression of production on input use may lead to biased coefficients. Second, if productivity shocks are serially correlated and firms exit the market after a negative shock, then any dataset of active firms will only contain those with relatively positive productivity shocks, again potentially biasing the results. Finally, a third challenge lies in the potential collinearity of variable and dynamic inputs. If firms choose variable inputs (e.g. labor or raw materials) as a deterministic function of dynamic state variables (e.g. capital), then the effect of these variable inputs may be impossible to separate from the dynamic inputs (Bond and Soderbom 2005).

These challenges have inspired a substantial literature on estimation techniques to recover the true parameters of production functions. One strand, beginning with Olley and Pakes (1996) has employed a control function approach to include proxies for a firm's productivity shock and propensity to exit within the estimation equation. Another approach, culminating in Blundell and Bond (2000) applies dynamic panel techniques to production function estimation, using lagged differences of variable and dynamic inputs as instruments in a GMM framework. Finally, DMW's approach advances the literature on instrumental variables estimates of production functions, a literature that has previously been hindered by the lack of plausible instruments with substantial interfirm variation (Ackerberg, Benkard, Berry, and Pakes 2007).

DMW resolve this difficulty by giving randomly selected firms lump sums of money or physical materials or capital, then using these random grants as instruments for capital in the production function. Firms were divided into four groups, receiving either 10,000 LKR in cash, 20,000 LKR cash, 10,000 LKR worth of materials or capital, or 20,000 LKR of materials or capital. This randomized approach is uniquely feasible in DMW's setting of microenterprises in Sri Lanka, since the firms are small enough (all had total non-building/land capital of less than 100,000 LKR) that the sums of money randomly allocated by the researchers represent a substantial cash shock.

This paper compares the randomized and structural estimation techniques using the same dataset of microenterprises used in DMW. Despite concerns of potential misspecification of both estimators, I find the results to be broadly similar, suggesting a role for structural estimation of production functions to reveal more insights into firms in developing economies. Section 1 develops a simple and standard model of firm production, and introduces the structural and IV estimators in the context of this model. Section 3 reviews the techniques for instrumental variables and structural estimation of production functions and discusses their application in the context of incomplete markets. Finally, section 4 provides a brief overview of the data, including some summary statistics that may inform the models, then presents and contrasts the results of each of the estimators.

1 Dynamic Firm Production

In order to motivate the estimation procedures, as well as to assist in intepreting the resulting parameters, this section lays out a model of a micro-entrepreneur solving a dynamic consumption and investment problem subject to random productivity and liquidity shocks[1]. The entrepreneur maximizes her discounted lifetime flow of consumption $\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^{t}u\left(c_{t}\right)\right]$where $u\left(c_{t}\right)$ is an increasing and concave utility function. She enters each period with some financial assets $A_t$and physical capital K_t, then earns the return on the assets $\left(1+r\right)A_t$ and operates his business, earning profits of π_t, defined as

$$\pi_t = F\left(K_t, X_t, \omega_t\right) - pX_t$$

where $F\left(K_t, X_t, \omega_t\right)$ is the production function transforming capital, K_t and a vector of static inputs, X_t (e.g. materials, labor, fuels, etc.) into a final good sold at a price normalized to 1[2]. The definition of profit used here and throughout the paper does not include the rental cost of capital employed, rK_t, a formulation that seems to correspond to that used by the surveyed entrepreneurs, only 1.9% of whom reported paying any rent for machinery or equipment in a given period.

A random period-specific productivity shock, ω_t is realized at the beginning of each period but unknown to the entrepreneur in advance. I allow these productivity shocks to be serially correlated, thereby including, at the extreme case of $\omega_t = \omega_{t-1}$,

[1]While all the substantive insights of the model also hold in a static setting, the identification of the structural estimators in section 3 depends critically on the timing of productivity shocks and capital accumulation across periods. Hence for consistency I present the firm's problem as dynamic in this section as well.

[2]The model presented here does not allow entrepreneurs to shut down their firms and exit the market. Introducing this option would change little of substance for the conditions determining capital and input use for those firms selecting to remain in the market (Pakes 1996) while substantially increasing the notation. The exit choice is discussed further in section 3, and the structural techniques discussed there allow for this possibility.

the possibility of firm-level fixed effects. Entrepreneurs also receive an IID liquidity shock Z_t, which could represent an unexpected cash transfer such as an inheritance, or in this context, the randomized transfer from the researchers. Finally, at the end of the period the owner of the firm invests in capital that is realized next period, and chooses how much to save and consume. Capital depreciates between periods at rate δ and thus evolves according to

$$K_{t+1} = (1-\delta) K_t + i_t$$

where i_t is the investment made in period t. Rewriting the entrepreneur's problem in recursive form yields

$$V(A_t, K_t, \omega_t) = \max_{X, K_{t+1} A_{t+1}} u(c_t) + \beta E[V(A_{t+1}, K_{t+1}, \omega_{t+1}) \mid \mid \omega]$$

subject to

$$c_t = F(K_t, X_t, \omega_t) - pX_t + (1+r) A_t - A_{t+1} + K_{t+1} - (1-\delta) K_t + Z_t$$

where the potential for serial correlation in the productivity shocks, ω_t, necessitates their inclusion in the vector of state variables. Solving for the entrepreneur's choice of investment and savings leads to the standard Euler equation and solution for the marginal return to capital,

$$\begin{aligned} \frac{u'(c_t)}{E[u'(c_t) \mid \omega_t]} &= \beta(1+r) && (1) \\ rE[u'(c_{t+1}) \mid \omega_t] &= E[(F_1'(K_{t+1}, X_{t+1}, \omega_{t+1}) - \delta) u'(c_{t+1}) \mid \omega_t] && (2) \\ F_2'(K_t, X_t, \omega_t) &= p && (3) \end{aligned}$$

In the case of perfect insurance markets, the condition determining investment (equation 2) reduces to

$$\mathbb{E}[F_1'(K_{t+1}, X_{t+1}, \omega_{t+1}) \mid \omega_t] = r + \delta$$

and investment is chosen to set the future expected returns to capital equal to the depreciation-adjusted interest rate. The current period liquidity shock does not affect the entrepreneur's choices of capital or inputs, and DMW's randomized one-time grants of cash to firms would be allocated primarily to savings, a prediction not born out in the data where only 12% of grant recipients chose to save the amount they have been given. Recipients of grants in the form of materials or capital might increase their production if they could not resell their granted stocks, but returns would be below the market interest rate, a prediction that DMW argue conflicts with the results found in the data.

While cash shocks should have no impact on production if markets are complete, the productivity shock directly affects the choice of X_t and, if these shocks are serially correlated, also the choice of next period's capital stock. Pakes (1996) shows that if the production function has increasing differences in K_t and ω_t, then investment will be monotonically increasing in the ω_t shock. OLS estimates of the return to capital generated by naive regressions of output on observed K_t and X_t will typically be biased upwards by the endogeneity of the capital choice-the original observation that inspired the literature on structural estimation of production functions.

The simple conditions derived above are founded upon the assumption of complete credit markets, an assumption that DMW (among others) argue is unlikely to hold for the microenterprises found in the Sri Lankan data. More plausibly, these firms face some constraints on their borrowing, constraints that I model as the limiting the total inputs and investment purchased for the business to being less than some multiplier λ of the firm's current assets, capital, and liquidity shock:

$$i_t + pX_t \leq \lambda \left(A_t + K_t + Z_t \right) \tag{4}$$

If this constraint binds, the convenient separation between the entrepreneur's cash shocks and the production process no longer holds. In particular, investment is determined by the condition

$$\mathbb{E}\left[u'\left(c_{t+1}\right) F_1'\left(K_{t+1}, X_{t+1}, \omega_{t+1}\right) \mid \omega_t \right] \quad = \quad \left(r+\delta\right) \mathbb{E}\left[u'\left(c_{t+1}\right) \mid \omega_t \right] + \frac{\mu_t - \beta\left(1-\delta\right) \mathbb{E}\left[\mu_{t+1} \mid \omega_t \right]}{\beta}$$

where μ_t and μ_{t+1} are the Lagrange multipliers on the current and future credit constraints.

The current period cash shock Z_t now affects capital choice by loosening the current period credit constraint, thereby decreasing the Lagrange multiplier, decreasing the optimal future returns to capital, and increasing current period investment. If there is any heterogeneity across firms, either in the current productivity shock or in the degree to which firms are credit constrained, the effects of the random grant on investment will vary across firms in a manner correlated with the returns to capital.

A similar condition defines the firm's choice of static inputs,

$$F_2'\left(K_t, X_t, \omega_t\right) = p\left(1 + \frac{\mu_t}{u'\left(c_t\right)}\right) \tag{5}$$

whose marginal return may also be set above cost if credit constraints are binding. Again, the random grant will increase input use, potentially to a heterogenous extent across firms, if there is any heterogeneity in K_t, A_t, or ω_t.

2 Reduced Form and IV Estimation of Production functions

Perhaps the main benefit of the randomized experiment of giving grants to microenterprises is that it allows for a direct and robust reduced form regression of firm profits on the size of the random grant given to the firm,

$$\pi_{it} = \gamma_0 + \gamma_1 Z_{it} + \varepsilon_{it}$$

where (assuming for the moment that there is continuous variation in the grant amounts, Z_{it}) the γ_1 coefficient expresses the return to additional funds. Expressing this coefficient in terms of the model developed above, I fully differentiate profits with respect to Z_t,

$$\begin{aligned} \frac{d\pi_{t+1}}{dZ_t} &= \frac{d}{dZ_t}\left(F\left(K_{t+1}, X_{t+1}, \omega_{t+1}\right) - pX_{t+1}\right) \\ &= \frac{\partial F\left(K_{t+1}, X_{t+1}, \omega_{t+1}\right)}{\partial K_{t+1}}\frac{\partial K_{t+1}}{\partial Z_t} + \frac{\partial F\left(K_{t+1}, X_{t+1}, \omega_{t+1}\right)}{\partial X_{t+1}}\frac{\partial X_{t+1}}{\partial Z_t} - p\frac{\partial X_{t+1}}{\partial Z_t} \end{aligned} \tag{6}$$

Equation 6 makes clear that the reduced form parameter differs substantially from the literal form of the return to capital $\partial F\left(K_t, X_t \omega_t\right)/\partial K_t$. In particular, even if the returns to fixed capital are zero, credit constrained firms' will still rise after receiving the grant due to increased purchases of materials, inventories, or labor. DMW report that 57% of entrepreneurs chose to purchase inventories or raw materials, consistent with a scenario in which returns to additional fixed capital may be low relative to the return to materials. Finally, recall that under complete markets one should expect γ_1 to be exactly zero, since any cash windfall should be saved rather than invested in the firm–that DMW find γ_1 to be both economically and statistically significant indicates the presence of substantial market imperfections.

The γ_1 coefficient, or $\frac{d\pi_{t+1}}{dZ_t}$, is an important parameter for policy purposes: it is revealing of the total extent of market imperfections, and, as DMW note, it indicates the total amount that microenterprises would benefit from a government subsidy or a microfinance loan. Furthermore, the robust estimation of $\frac{d\pi_{t+1}}{dZ_t}$ that comes directly from a randomized trial could not easily be derived from through structural estimation, since it depends on the entrepreneur's investment policy function which is itself a function of many unidentified parameters such as δ, β, λ, the form of the utility function, etc. However, knowledge of γ_1 tells us little about the underlying production functions of the microenterprises. To isolate the direct effect of capital on profits, DMW specify a 2SLS regression of profits on capital (in levels), with capital instrumented by the Sri Lankan rupee value of the randomly allocated grant to the firm, and including firm and year fixed effects,

$$\begin{aligned} \pi_{it} &= \beta_0 + \beta_1 K_{it} + \eta_i + \psi_t + \varepsilon_{it} \\ K_{it} &= \alpha_0 + \alpha_1 Z_{it} + \zeta_i + \phi_t + \varepsilon_{it} \end{aligned}$$

where as usual it is assumed that firms' reported profits does not include the rental rate on their fixed capital.

Under certain conditions discussed in detail below, the coefficient β_1 from this regression corresponds to the full differential of profits with respect to capital: the change in firms' profits with respect to an increase in capital, including the effects of any changes in labor or static inputs due to that change in capital. Under complete markets the first stage should be insignificant if Z_{it} is a pure cash grant, but assuming some effect of Z_{it} on K_{it} due to optimization error or because some grants were given in the form of capital, we should expect that $\beta_1 = r$ since firms should borrow to purchase capital until its returns in terms of profits are equal to the interest rate[3].

The relationship between the β_1 parameter and the return to capital becomes substantially less clear under incomplete markets. The randomized grant program provides a single instrument, one which affects not only capital choice but also other endogenous variables such as the amount of labor and intermediate inputs purchased. Using profit as a dependent variable resolves this issue under the assumption of perfect labor and intermediate input markets, since the coefficients of a regression of revenue on the static inputs should simply be equal to cost of these inputs, which can then

[3]Under complete markets the partial and full derivatives of profits with respect to capital should be equal, since all other inputs are used to the point where their marginal benefit is exactly equal to their cost, and thus by the envelope theorem a change in capital stock should have no indirect effects. Under incomplete markets, and in particular in the case outlined in section 1 where the credit constraint and hence the degree of market imperfection depends on the capital stock, this equivalence will no longer hold.

be subtracted from both sides of the equation to yield DMW's prefered specification with profit (not including capital costs) as the dependent variable,

$$\begin{aligned} Y_{it} &= \beta_0 + \beta_1 K_{it} + \beta_2 X_{it} + \eta_i + \gamma_t + \varepsilon_{it} \\ Y_{it} - pX_{it} &= \beta_0 + \beta_1 K_{it} + (\beta_2 X_{it} - pX_{it}) + \eta_i + \gamma_t + \varepsilon_{it} \\ \pi_{it} &= \beta_0 + \beta_1 K_{it} + \eta_i + \gamma_t + \varepsilon_{it} \end{aligned}$$

In the absence of perfect intermediate input markets, or if firms are credit constrained in their choice of X_{it} as in the model in section 1, $\beta_2 \neq p$, and it is the shadow costs of inputs that must be subtracted from output to yield consistent estimates of β_1. While DMW carefully consider these issues when subtracting the value of the entrepreneurs' own wages from their reported profits, it is unlikely the entrepreneurs themselves went to the same pains to account for the shadow cost of other static inputs when reporting their own profits. The IV coefficient on capital stock is then

$$\begin{aligned} \hat{\beta}^{IV} &= \frac{\operatorname{cov}(\pi_{it}, Z_{it})}{\operatorname{cov}(K_{it}, Z_{it})} \\ &= \beta_1 + (\beta_2 - p) \frac{\operatorname{cov}(X_{it}, Z_{it})}{\operatorname{cov}(K_{it}, Z_{it})} \end{aligned}$$

Substituting the return to intermediate inputs from equation 5 for β_2 and cancelling yields

$$\hat{\beta}^{IV} = \beta_1 + \left(\frac{\mu_t}{u'(c_t)} \right) \frac{\operatorname{cov}(X_{it}, Z_{it})}{\operatorname{cov}(K_{it}, Z_{it})}$$

which shows that the bias in the IV parameter is an increasing function of the Lagrange multiplier on the credit constraint. Thus under a standard model of credit constraints the 2SLS regression of profits on only capital instrumented by the random grant does not yield the true return to capital.

There are several possible means to deal with this ommitted variable bias. The solution chosen by DMW is to introduce fixed effects to control for the time invariant component of $(\beta_2 - p) X_{it}$. However, this method will only work if variable input use, X_{it} is relatively constant within a firm, which does not appear to be the case for the Sri Lankan microenterprises. A more effective technique would be to introduce another instrument for X_{it}. Since DMW distributed four different types of grants, this approach is, in principal, feasible if at least two of the grant types induced independent variation in K_{it} and X_{it} and can then be used as seperate instruments. Unfortunately, as is clear from table 3, the first stage regressions of input use on dummy variables for the different grant types are sufficiently noisy that is impossible to statistically distinguish the effects of the different types of grants on different inputs despite point estimates that are often substantially different. Though one may still attempt to use the different grants to identify the effects of different inputs seperately, the standard errors on the resulting second stage estimates will be large due to the collinearity induced by the similar instruments (see, for example, tables 6 and 7).

Another potential difficulty in the interpretation of the IV estimate of the returns to capital arises when there is heterogeneity in the response of individual agents to treatment programs. As DMW themselves point out, under heterogeneous treatment effects IV and OLS estimators generally converge to different probability limits, corresponding to differently weighted averages of the underlying structural parameters. In particular, if the model is correctly specified, the coefficients from the LP approach correspond to OLS estimates of the returns for capital controlling for the unobserved productivity shock, while the coefficients reported by DMW are the result of 2SLS using the experimental capital grant as an instrument.

These issues are particularly relevant in this context, since many authors (Banerjee and Duflo 2009) have argued that heterogeneity in the returns to capital is a central feature of markets in developing countries. Indeed, the substantial literature on capital misallocation is founded on this premise, and it seems a plausible hypothesis in the context of Sri Lankan microenterprises where financial institutions to redistribute capital to the most productive firms may be lacking. DMW investigate the possibility of heterogeneous returns, but argue that these returns appear to be uncorrelated with the changes in firms' capital levels induced by the random grants. In support of this argument they show that the percentage of the grant invested appears uncorrelated with variables that predict higher returns, for instance proxies for entrepreneur ability, risk aversion, or past profit/capital stock ratios. While reassuring, these results are not entirely robust to the type of serially correlated productivity shocks ω_t presented in section 1, which would affect both current output and future capital investment due to the random grant.

To investigate these issues further, consider the a regression of profits on capital, controlling for other inputs and (assuming it can be observed) the productivity shock,

$$\mathbb{E}\left[\pi_{it} \mid X_{it}, \omega_{it}\right] = a + b\mathbb{E}\left[K_{it} \mid X_{it}, \omega_{it}\right]$$

The standard OLS coefficient is,

$$\hat{b}^{OLS} = \frac{\text{cov}\left(\pi_{it}, K_{it} \mid X_{it}, \omega_{it}\right)}{\text{var}\left(K_{it}|X_{it}, \omega_{it}\right)}$$

Following Yitzhaki (1996), the OLS coefficient can be shown to be a weighted average of the returns to capital on profits. Leaving off the conditioning on X_{it} and ω_{it} for conciseness, he shows that,

$$\hat{b}^{OLS} = \frac{1}{\text{var}\left(K_{it}\right)} \int_{-\infty}^{\infty} \frac{\partial \mathbb{E}\left[\pi_{it}|K\right]}{\partial K} w^{OLS}\left(K\right) dK$$

where the OLS weighting function $w^{OLS}\left(K\right)$is

$$w^{OLS}\left(K\right) = \int_{K}^{\infty} \left(\kappa - \mathbb{E}\left[K\right]\right) f_K\left(\kappa\right) d\kappa$$

In the standard case in which the returns to capital are homogeneous, $\frac{\partial \mathbb{E}[\pi_{it}|K]}{\partial K} = \beta$, and the estimator returns the standard OLS result $\hat{b}^{OLS} = \beta$. Alternatively, it is possible that the firm's returns to capital are uncorrelated with their capital levels, for instance in the case where productivity is a IID random variable, and in this case OLS returns $\hat{b}^{OLS} = \int_{-\infty}^{\infty} \frac{\partial \mathbb{E}[\pi_{it}|K]}{\partial K} dK = \bar{\beta}$. Otherwise, the OLS estimator returns a weighted average of the heterogeneous returns, with greater weights on observations with K_{it} values closer to the mean.

A similar set of calculations yields the IV estimator

$$\begin{aligned}
\hat{\beta}^{IV} &= \frac{\text{cov}\left(\pi_{it}, Z_{it} \mid X_{it}, \omega_{it}\right)}{\text{cov}\left(K_{it}, Z_{it} \mid X_{it}, \omega_{it}\right)} \\
&= \frac{1}{\text{cov}\left(K_{it}, Z_{it}\right)} \int_{-\infty}^{\infty} \frac{\partial \mathbb{E}\left[\pi_{it}|Z\right]}{\partial Z} \int_{Z}^{\infty} \left(\zeta - \mathbb{E}\left[Z\right]\right) f_K\left(\zeta\right) d\zeta dZ
\end{aligned}$$

In general $\hat{\beta}^{OLS} \neq \hat{\beta}^{IV}$, although in the two special cases considered above, homogeneous returns and returns uncorrelated with capital levels, the two estimators will converge to the same results.

A canonical (albeit very specific) case in which many of the problems of heterogeneity are easily resolved is when firms' output has constant elasticity with respect to inputs, as is the case for a Cobb Douglas production function. If all firms have the same Cobb Douglas production function, a log transformation of output and all inputs will remove any heterogeneity due to capital misallocation, and the structural parameters of the production can be recovered directly from the coefficients on the log inputs (assuming any endogeneity issues are resolved). In light of this result, the most robust test of the structural estimators may be to compare IV and structural regressions specified in logs; nevertheless heterogeneity remains a concern since it is possible that firms may be heterogeneous both in returns to capital and in the elasticity of revenue with respect to capital

3 Structural Estimation of Production Functions

Starting with Olley and Pakes (1996) a substantial literature has developed on structural estimation of the parameters of production functions using control functions to account for unobserved productivity shocks. In this section I review these techniques as applied to the problem of estimating the production functions of the Sri Lankan microenterprises, largely following the presentation of Levinsohn and Petrin (2003) (henceforth LP) in Ackerberg, Caves, and Frazer (2006)[4] (henceforth ACF). For brevity of notation, firms' production functions are modeled as Cobb Douglas, and intermediate inputs are limited to labor l_{it} and materials m_{it}. Output, y_{it}, is then

$$\log\left(F\left(K_t, X_t, \omega_t\right)\right) = \quad y_{it} = \quad \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \tag{7}$$

where ω_{it} is, as described above, a productivity shock observed by the firm, and ε_{it} is an IID shock to output unobserved by the firm before output is realized, potentially representing measurement error. The assumption of a Cobb Douglas functional form is not essential to the estimation technique, and will be relaxed in the empirical section.

Consistent with the model presented above, firms are assumed to choose capital in a previous period ($t-1$ or earlier), and observe the current period productivity shock at the beginning of each period. I further augment the dynamics of the model developed in section 1 to allow firms the option to exit the market after learning their productivity realization, ω_t. Firms will avail themselves of this exit option if the current productivity shock is low enough that the expected returns of remaining in business are below the sell-off value of the firm. Following Olley and Pakes, the solution to the firm's exit decision can then be modelled as an indicator function χ_t equal to one if the firm remains in business, and a cut-off value of the productivity

[4]The assumptions underlying the original estimation technique developed by Olley and Pakes are such that the method may only be used on observations containing non-zero investment. Since only 11% of the firm-survey rounds in the DMW Sri Lankan firm dataset satisfy this condition, I focus on techniques developed by Levinsohn and Petrin (2003) and Ackerberg, Caves, and Frazer (2006) that do not impose this requirement.

shock $\underline{\omega}_t(k_t)$ such that

$$\chi_{it} = \begin{cases} 1 & \text{if } \omega_{it} \geq \underline{\omega}(k_{it}) \\ 0 & \text{otherwise} \end{cases}$$

The selection on unobservables inherent in the firms' exit decision introduces another potential source of bias. Olley and Pakes show that if firms' gains from staying open during a bad shock are increasing in the size of their capital stock, then $\underline{\omega}(k_{it})$ will be decreasing in k_{it} and low productivity realizations will only be observed for firms with large k_{it}. The ensuing negative correlation between ω_{it} and k_{it} will thus bias downward the coefficient on capital.

After the exit decision has been made, firms that decide to remain in the market simultaneously select labor and material inputs. LP's estimation technique is based on the observation that in perfect markets the firm's choice of intermediate inputs

$$m_{it} = \iota(k_{it}, \omega_{it})$$

will be monotonically increasing in the productivity shock under a wide variety of conditions. However, with credit constraints or other market imperfections, this montonicity may only hold conditional on other variables[5]. For instance, in the model in section 1, equation 5 shows the choice of inputs X_{it} to be a function not only of K_{it} and ω_{it}, but also of the marginal utility and the Lagrange multiplier. While in this particular model expanding the intermediate input function to include A_{it} and Z_{it} would restore conditional monotonicity, the broader point is that monotonicity cannot be taken for granted in models of imperfect markets.

Maintaining the monotonicity hypothesis (while bearing this caveat in mind), the intermediate input function can be inverted to generate a proxy for unobserved productivity as a function of the observed choices of capital and intermediate inputs

$$\omega_{it} = \iota^{-1}(k_{it}, m_{it}) \tag{8}$$

While the form of the $\iota^{-1}(\cdot)$ function is generally unspecified, it can be approximated by a nonparametric function of capital and intermediate inputs, $g(k_{it}, m_{it})$ (either using a high order polynomial or a local linear regression) and this proxy function

[5] I thank Michael Peters for bringing this issue to my attention

can be substituted for the productivity shocks in equation 7 to yield

$$\begin{aligned} y_{it} &= \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + g\left(k_{it}, m_{it}\right) + \varepsilon_{it} \\ &= \beta_l l_{it} + \Phi\left(k_{it}, m_{it}\right) + \varepsilon_{it} \end{aligned} \tag{9}$$

Given some source of exogenous variation in l_{it} (a point discussed further below), a regression of y_{it} on l_{it} and this non-parametric function of k_{it} and m_{it} yields a consistent estimate of β_l, but leaves β_k and β_m unidentified. These parameters can, however, be identified by the timing assumptions that current period capital stock and previous period variable input choices are uncorrelated with the current period innovation in the productivity shock. Let this innovation be defined as ξ_t, where

$$\xi_{it} = \omega_{it} - \mathbb{E}\left[\omega_{it} | \omega_{t-1}, k_{it}, \chi_{it} = 1\right] \tag{10}$$

Equation 10 demonstrates again the importance of incorporating the exit decision into the estimation procedure, since firms with low current capital stock may be expected to have higher future productivities if they choose to continue operation. OP show that the final term, the expectation of the current productivity shock conditional on the firm's continued operation, can be expressed as a function of the lagged survival probability of the firm, $P_{t-1} = \Pr\left\{\chi_t = 1 \mid \underline{\omega}_t\left(k_t\right), \omega_{t-1}\right\}$, and the lagged productivity shock,

$$\begin{aligned} \mathbb{E}\left[\omega_{it} | \omega_{t-1}, k_{it-1}, \chi_{it} = 1\right] &= j\left(\underline{\omega}_t\left(k_t\right), \omega_{t-1}\right) \\ &= j\left(P_{t-1}, \omega_{t-1}\right) \end{aligned}$$

which follows from the fact that the survival probability can be represented as a function of the productivity cut-off $\underline{\omega}_t\left(k_t\right)$ which can then be inverted and the resulting expression for $\underline{\omega}_t\left(k_t\right)$ in terms of P_{t-1} substituted into the $j\left(\cdot\right)$ function.

LP show that, conditional on coefficients for the capital and materials parameters, both $\hat{\omega}_{it}\left(\beta_k, \beta_l\right)$ and $\hat{\xi}_t\left(\beta_k, \beta_l\right)$ can be recovered using the results of the first stage estimates: $\hat{\omega}_{it}\left(\beta_k, \beta_l\right)$ from the relation

$$\hat{\omega}_t\left(\beta_k, \beta_l\right) = \hat{\Phi}\left(k_{it}, m_{it}\right) - \beta_k k_{it} - \beta_m m_{it}$$

and $\hat{\xi}_t\left(\beta_k, \beta_l\right)$ from the residuals of a regression of $\hat{\omega}_t$ on a nonparametric function

$h(\cdot)$ of $\hat{\omega}_{t-1}$ (again by either local linear regression or polynomials):

$$\hat{\omega}_t(\beta_k, \beta_l) = h\left(\hat{P}_t, \hat{\omega}_{t-1}(\beta_k, \beta_l)\right) + \hat{\xi}_t$$

where $\hat{P}_t$ is the predicted survival probabilities from a first stage non-parametric regression of χ_{it} on k_{it-1} and i_{it-1}.

Finally, the capital and intermediate input parameters are chosen to set these productivity innovations to be uncorrelated with current capital stock and past period intermediate inputs, generating the moment conditions,

$$\mathbb{E}\left[\xi_{it}(\beta_k, \beta_l) \cdot \begin{pmatrix} k_{it} \\ m_{it-1} \end{pmatrix}\right] = 0$$

A key element of this estimation strategy is the presence of a source of variation in l_{it} which is independent of the other factors of production, but does not directly affect output or expectations of future returns to labor or capital. Without this, as ACF demonstrate, the β_l coefficient will not be identified in equation 9. While ACF are skeptical that such variation exists, it may indeed be present in the context of the Sri Lankan microenterprise data. DMW document that firms frequently purchase materials several months prior to using them in the production process, whereas labor, in particular labor of the business owner herself, may be more flexibly decided after the purchase of inputs and subject to shocks to the business owner's opportunity cost of time.

Nevertheless, in the absence of independent variation in l_{it}, ACF propose an estimation strategy that allows for the alternative, perhaps more realistic production process in which labor is still determined after intermediate input production, but the choice of labor is correlated with the productivity shock. More formally, assume that each period has an intermediate stage, at time $t-b$, when intermediate inputs m_{t-b} are purchased, and that the productivity shock ω_{it} evolves according to a first order Markov process between these stages, i.e.

$$p(\omega_{it}|I_{it-b}) = p(\omega_{it}|\omega_{it-b}) \text{ and } p(\omega_{it-b}|I_{it-1}) = p(\omega_{it-b}|\omega_{it-1})$$

In this case labor use is a function of both the productivity shock, and the time $t-b$ choice of materials, and these factors must now enter into the inversion used to recover ω_t,

$$\omega_t = g\left(k_{it}, m_{it-b}, l_{it}\right)$$

Substituting this new augmented function into equation 9 makes it clear that the coefficient on labor is no longer identified in the first stage. However, the second stage may proceed as in the Levinsohn-Petrin procedure, with the productivity shocks recovered, conditional on a set the $\{\beta_k, \beta_l, \beta_m\}$ parameters from

$$\hat{\omega}_t\left(\beta_k, \beta_l\right) = \hat{\Phi}\left(k_{it}, m_{it}, l_{it}\right) - \beta_k k_{it} - \beta_l l_{it} - \beta_m m_{it}$$

and the final moment conditions of

$$\mathbb{E}\left[\xi_{it}\left(\beta_k, \beta_l, \beta_m\right) \cdot \begin{pmatrix} k_{it} \\ m_{it-1} \\ l_{it-1} \end{pmatrix}\right] = 0$$

While these techniques account for several potential sources of bias, they rely on assumptions about the timing and shocks to the production process; (Bond and Soderbom 2005) assumptions that have remained largely untested due to the lack of a clear baseline.

4 Sri Lankan Microenterprise Data and Results

DMW provide a detailed description of the data collection and randomized allocation of grants to microenterprises in their main paper, as well as additional details in a companion paper on measuring firm profits (De Mel, McKenzie, and Woodruff 2008a). In this section I briefly review the setting and approach of their experiment, as well as report some summary statistics of particular interest in the context of structural estimation of production functions. Readers interested in learning more are encouraged to refer to the more detailed descriptions in DMW's original work.

DMW's preferred sample contains data on 408 enterprises operating in southern and southwestern Sri Lanka in April 2005. [6] The owner/managers of these firms were selected from a baseline household census, on the criterion that they were self-employed workers outside of agriculture, fishing, transportation, and professional services, between the ages of 20 and 65, had less than 100,000 LKR in capital (about

[6] The full dataset, including those directly affected by the tsunami, contains 618 firms. I restrict the sample to that used by DMW for ease of comparability.

\$1000) net of land and buildings, had no paid employees, and were not directly affected by the December 2004 tsunami. The selected firms were roughly evenly split between retail sales establishments (203 firms), typically small grocery stores, and manufacturing firms (205 firms). There is substantial variety in the primary output of the manufacturing firms, with the most common activities being sewing clothes (62 firms), food production (38 firms), spinning lace (36 firms) and making bamboo products (29 firms).

The sample firms were interviewed quarterly for over two years, for a total of nine rounds of data in DMW's preferred sample. In each survey round, the firm owners were administered a detailed questionnaire in which they reported expenditures on materials, labor, inventories and investment, as well as revenues and profits. There is a substantial discrepancy between reported profits and profits implied by reported revenues and expenditure. DMW (2008a) investigate this discrepancy and attribute it largely due to mis-timing of purchasing of materials and inventories versus sales of finished goods.

The richness of the data yields a variety of variables that could serve as proxies for the unobserved productivity shock. All firms report hours of labor used by both the entrepreneur himself or herself, the hours of family labor, and the hours of paid non-family labor. In the presence of credit constraints perhaps the most promising of these is the firm owner's own labor, since this is both very flexible and hence likely to be correlated with current period productivity, as well as relatively unlikely to be constrained by financial frictions. The quantity of materials purchased during the past month is another potential proxy, as is the amount of fuel/electricity used, although both of these may fail the monotonicity condition if highly credit constrained firms with large positive productivity shocks purchase less of them than unconstrained firms with lower productivity shocks. Another potential proxy comes from the survey question that asked entrepreneurs how much of the material inputs purchased during the past month had actually been transformed into outputs and sold during that month: as long as firms use less inputs than their total purchased amount (true in 92% of firm/survey round observations), this quantity may be relatively less affected by credit constraints.

Firm exit occurs relatively frequently in the microenterprise data: of the 385 firms in the DMW sample, there are 73 cases in which firm owners report changing their line of business from what had been their activity during the previous survey firm visit. Exit occurs for a variety of reasons tabulated on table 2, the most commonly specified (25 cases) being that the business was making a loss. These may to be cases where, much as in Olley and Pakes' model, firms experiencing negative productivity shocks exit the market. 10 firms exited due to sickness of the entrepreneur, which might be interpreted as a positive shock to the cost of labor (and a shock which, under perfect markets, we would not expect to affect the firm). Exit from one business did not necessarily imply a permanent exit from entrepreneurship: 30 of the 73 entrepreneurs in the sample who exited or switched businesses subsequently began new businesses with some non-land or building based capital.

4.1 Results

To establish a baseline against which to compare the IV and structural estimators of production functions, I first estimate OLS regressions of revenue and profits on capital, variable inputs, and other entrepreneur characteristics, and present the results (using only data from firms in the control group) in tables 4 and 5. The most striking feature of the OLS regressions of revenue on inputs in table 4 is the lack of effect of including labor (total hours of family plus hired labor used in the past week) in the regression on the capital coefficient. In specifications with either revenue in levels (columns 1 and 2) or in logs (columns 6 and 7) as the dependent variable, the inclusion of labor in the regression has no significant effect on the capital coefficient, suggesting a lack of complementarities between capital and labor. This result contrasts markedly with the predictions of the canonical Cobb Douglas production function, where the effect of introducing labor into the log-revenue specification (abstracting from concerns about endogeneity or credit constraints) should be to scale the capital coefficient by one minus the coefficient on labor. Results for other variable inputs are more in line with standard predictions: controlling for materials and inventory use in columns 4 and 9 substantially decreases both labor and capital coefficients. Introducing fixed effects reduces the capital and materials coefficients but has little effect on the estimated labor coefficient.

OLS regressions of profits on variable inputs and capital in table 5 are qualitatively similar, although of course subject to the same strong caveats of endogenity that make the results difficult to interpret[7]. Again, labor seems almost uncorrelated with capital use, which is strongly correlated with materials. Introducing firm-level fixed effects in columns 5 and 10 substantially reduces the capital coefficient, making it insignificant in the regression on capital in levels. As DMW note, women appear, on average, to

[7]DMW report a substantially lower coefficient on a capital in a regression similar to that in column 2. I find a higher result by including all un-treated firms in the sample (DMW use only data from the first round of data), and by using reported real profits instead of profits adjusted for owner's labor. Using the adjusted profits in the same sample reduces the coefficient to 3.79 (0.558).

earn lower profits than men, and curiously education and owner age are significant and negative in some specifications.

Tables 6 and 7 present the same regressions, now using dummy variables for DMW's four treatment types (10,000 LKR cash grant, 10,000 LKR in-kind grant, 20,000 LKR cash grant, and 20,000 LKR in-kind grant) as instruments for endogenous inputs. Columns 1, 2, 6 and 7 of each table present regressions of revenues and profits (in levels and logs) on capital, controlling for fixed effects in columns 2 and 7. Both profit and revenue coefficients are substantially greater than the OLS coefficients, although these differences are not always significant due to the large 2SLS standard errors. Including fixed effects (DMW's preferred specification) appears to lower the estimated effect of capital on output; again the differences between fixed effects and OLS coefficients are not significant. Finally, the remaining columns of tables 6 and 7 document the largely uninformative attempt to use the difference in grant types to seperately identify the effect of different inputs in order to control for potential endogeneity due to the difference between the accounting and shadow cost of inputs. Standard errors are extremely high on all variables, suggesting substantial collinarity in the second stage.

Univariate structural estimation of the effect of capital on profits and revenues (in levels and logs) is presented in table 8. Structural results are remarkably stable across specifications and quantitatively similar to the fixed-effects IV and non-fixed effects OLS regressions. Indeed, in no case are the structural estimates statistically different from the IV coefficients, although this is partly due to the large standard errors in the IV[8]. Given the concerns raised in section 2 with heterogeneity and potential correlation between the instrument and the residual contribution of materials to profits (net of the materials cost), the most robust IV parameter may be the fixed effects estimate of profit in logs on log capital, 0.310 (0.124). This is roughly 21% lower than full-sample structural estimate of the same parameter, 0.396 (0.039), and statistically indistiguishable from it. Interestingly, the IV coefficient on capital in a regression not including is almost 50% larger than the IV-FE coefficient, which suggests that the fixed effect may indeed be capturing residual variation correlated with the random shock.

Comparing coefficients across columns, it seems that all three proxies yield similar results, with no obvious trends across specifications. Figures 1, 2, and 3 investigate the

[8]Since the Levinsohn & Petrin method and the Ackerberg, Caves, & Frazer technique coincide when the only independent variable is capital, these results tell us little about the choice of structural technique.

choice of proxy further, plotting the predicted productivity shock (ω_t) as a function of capital and the candidate proxy variable. Recall that for the inversion in equation 8 to recover the productivity shock, the shock must be monotonically increasing in the proxy. This monotonicity is very clear for materials and inventories in figure 1, seems to hold for the fraction of materials and inventories purchased in the last month that were used displayed in 2, but does not appear to hold for the owner's hours worked in figure 3. In light of these results, subsequent specifications use materials and inventories as the proxy for productivity shocks.

The structural estimator, assuming it is properly specified, may be used to estimate the returns to the other inputs to production that cannot be identified with only a single instrument. Table 10 contains the results of this estimation for both the LP and ACF estimators. The results in columns 1 and 3, which do not control for entrepreneur characteristics, show little differences between the ACF and LP techniques, with the exception of the labor coefficient which is about twice as big using the ACF technique, although also estimated with substantially more noise. Materials and capital coefficients are very close between estimators and also very similar to the OLS results. This is consistent with LP and Olley and Pakes, who also find that the structural estimates are not typically statistically different from the OLS estimates. Controlling for entrepreneur characteristics substantially decreases all parameters except the capital coefficient, while increasing the standard errors. Women are still predicted to have lower productivity, and the coefficients on age and education are now positive and, in some specifications significant.

Table 11 uses the structural estimator to investigate the differences in production functions between sectors. The firms in the Sri Lanka dataset are divided into three broad sectors, manufacturing, trade, and services, and the elasticities of revenue with respect to capital, labor and materials are estimated seperately for each sector using the Levinsohn & Petrin estimator with materials and inventories as a proxy. Due to the decreased sample size I no longer include controls for entrepreneur characteristics. The result show substantial and occasionally significant differences between coefficients across sectors: as might be expected, firms in services sector (e.g. sewing clothes) have the highest elasticity with respect to materials and labor and a lower elasticity of fixed capital than those in manufacturing and trade, although these differences are not significant perhaps due to the relatively small number of observations of firms in services. Less intuitively, I find that the elasticity of labor is significantly lower in the trade sector, which consists mainly of retail shops (61%). The data is suggestive that returns to scale may be higher in the services sector, although the coefficients are estimated with too much error to reject the null hypothesis of constant returns in all sectors.

Conclusion

The choice of techniques to study the production processes of firms in developing countries ultimately depends upon the question that the researcher wishes to answer. DMW's reduced form estimate of the impact of a cash grant on profits answers a well-defined policy question, a question that would be impossible to answer through structural estimation without a host of additional assumptions on entrepreneur's utility functions, discount factors, and other unidentified parameters. Yet to investigate other questions, such as how structural changes in markets affect firms' productivities, or to delve deeper into questions about capital allocation and productivity differences across firms, a more complete parameterization of firms' production functions is can yield valuable insights. Under certain assumptions, the ACF and LP estimation techniques offer consistent estimates of these parameters, and DMW's Sri Lankan dataset provides a unique opportunity to compare these results with estimates derived from a randomized field experiment. I find the results to be similar in economic and statistical terms, a result that suggests that, under certain circumstances, structural estimators of production functions may be a valuable tool to learning more about production and firm growth in the developing world.

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Tables

Table 1: Summary Statistics

	Percent of non-missing observations	Mean	Std. Deviation	Median
Profits (real LKR)	96.15%	5970.23	5412.44	4063.31
Revenues (real LKR)	97.69%	22745.97	28368.29	11538.23
Material and Inventory costs (real LKR)*	96.62%	15936.98	23279.77	7448.64
Fuel and Electricity (real LKR)*	69.69%	352.08	607.87	143.71
Materials/Inventories used or sold (real LKR)*	82.30%	11398.54	21457.42	3600
Investment (real LKR)*	10.97%	8062.93	17960.96	2260.01
Capital excluding land and buildings (real LKR)	93.40%	37770.26	41359.90	26000
Own hours worked	100.00%	51.07	25.3	50
Family hours worked	100.00%	20.64	31.32	0
Paid labor hours worked	100.00%	3.97	18.43	0
Firms exiting	100.00%	0.02%	0.15	0

Values in Sri Lankan LKR are deflated by the Sri Lankan CPI to April 2005 values. Observations with absolute or proportional profit changes in the top 5% dropped.

* Percentage of missing observations include those for which these variables were equal to zero.

Table 2: Reasons for Firm Exit

Reason	Frequency	Percent of cases
The business was making a loss	25	34.25%
Sickness or health reasons	10	13.70%
I found a better paying wage job	5	6.85%
To take care of family matters	4	5.48%
A better business opportunity came along	2	2.74%
Other	27	36.99%
Total	73	100%

Exit occurs when the entrepreneur reports changing his or her line of business from the activity being performed at the last survey visit.

Table 3: Effect of Treatments on Input Use

Impact of treatment amount on:	Capital stock	Log capital stock	Owner hours worked	Log owner hours worked	Materials and inventories purchased	Log materials and inventories purchased
	1	2	3	4	5	6
10,000 LKR in-kind	4793.802*	0.399**	6.052**	0.132**	-703.263	0.334**
	(2713.579)	(0.077)	(2.856)	(0.061)	(1558.678)	(0.147)
20,000 LKR in-kind	13167.128**	0.715**	-0.581	0.043	6600.362*	0.344**
	(3773.485)	(0.169)	(3.414)	(0.066)	(3855.861)	(0.151)
10,000 LKR cash	10781.247**	0.230**	4.515*	0.092**	2200.728	0.233
	(5139.460)	(0.103)	(2.540)	(0.046)	(1692.130)	(0.162)
20,000 LKR cash	23431.369**	0.533**	2.365	0.041	3465.381	0.418**
	(6685.955)	(0.113)	(3.259)	(0.056)	(2945.594)	(0.134)
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.098	0.203	0.011	0.006	0.05	0.03
N	3156	3156	3379	3155	3320	3265

Capital stock and materials and inventories used are measured in Sri Lankan rupees, deflated by the Sri Lankan CPI to reflect March 2005 price levels. Standard errors clustered at the firm level in parentheses. **p < .05 *p < .10

Table 4: OLS Results- Revenue

	Revenue in Levels					Revenue in Logs				
	1	2	3	4	5	6	7	8	9	10
Capital	28.101**	26.596**	4.455**	4.277**	2.556	0.509**	0.471**	0.172**	0.181**	0.156**
	(3.711)	(3.715)	(1.934)	(1.893)	(2.345)	(0.044)	(0.040)	(0.032)	(0.032)	(0.045)
Labor		54.107**	16.964**	15.773**	13.059		0.450**	0.142**	0.140**	0.143**
		(12.285)	(7.177)	(7.061)	(8.872)		(0.070)	(0.049)	(0.045)	(0.041)
Materials			0.774**	0.768**	0.479**			0.527**	0.522**	0.280**
			(0.064)	(0.064)	(0.075)			(0.039)	(0.038)	(0.037)
Owner's age				27.422					-0.009	
				(43.742)					(0.109)	
Owner's education				39.726					-0.214**	
				(120.867)					(0.105)	
Female owner				-2337.027**					-0.149**	
				(832.088)					(0.059)	
Survey round fixed effects	No	No	No	No	Yes	No	No	No	No	Yes
Firm fixed effects	No	No	No	No	Yes	No	No	No	No	Yes
R^2	0.233	0.248	0.665	0.668	0.315	0.298	0.357	0.684	0.695	0.301
N	1714	1714	1714	1714	1714	1713	1660	1638	1592	1638

All regressions run DMW's preferred sample, further selected to include only control firms and firms that had as yet received no grant from the researchers. Dependent variable in columns 1-5 is real (CPI-adjusted) revenue in levels, and in columns 6-10 is real revenue in logs. Standard errors in parenthesis clustered at the firm level. ** p < .05 * p < .1

Table 5: OLS Results- Profit

	Profit in Levels					Profit in Logs				
	1	2	3	4	5	6	7	8	9	10
Capital	4.693**	4.310**	2.456**	2.304**	0.268	0.362**	0.331**	0.180**	0.179**	0.116**
	(0.602)	(0.573)	(0.637)	(0.594)	(0.762)	(0.030)	(0.028)	(0.030)	(0.031)	(0.040)
Labor		13.528**	10.403**	9.636**	8.432**		0.343**	0.180**	0.172**	0.203**
		(2.551)	(2.566)	(2.473)	(3.279)		(0.054)	(0.050)	(0.047)	(0.043)
Materials			0.065**	0.063**	0.038**			0.268**	0.264**	0.171**
			(0.013)	(0.012)	(0.011)			(0.032)	(0.030)	(0.032)
Owner's age				-31.778*					-0.209*	
				(16.581)					(0.122)	
Owner's education				-66.164					-0.264**	
				(50.511)					(0.112)	
Female owner				-1509.261**					-0.246**	
				(342.238)					(0.068)	
Survey round fixed effects	No	No	No	No	Yes	No	No	No	No	Yes
Firm fixed effects	No	No	No	No	Yes	No	No	No	No	Yes
R^2	0.105	0.177	0.245	0.279	0.092	0.146	0.299	0.259	0.465	0.118
N	1691	1691	1691	1691	1691	1472	1640	1411	1574	1411

All regressions run on DMW's preferred sample, further selected to include only control firms and firms that had as yet received no grant from the researchers. Dependent variable in columns 1-5 is real profits in levels, and in columns 6-10 is profits in logs. Profits not adjusted for firm owner's own labor or cost of capital. Standard errors in parenthesis clustered at the firm level. ** $p < .05$ * $p < .1$

Table 6: IV Results - Revenues

	Revenue in Levels					Revenue in Logs				
	1	2	3	4	5	6	7	8	9	10
Capital	47.981**	34.506**	48.857**	19.767	-0.433	0.894**	0.515**	0.905**	0.537	0.153
	(10.048)	(10.818)	(12.015)	(17.491)	(23.580)	(0.157)	(0.149)	(0.156)	(0.444)	(0.706)
Labor			-288.096		209.282			-0.154		1.224
			(245.440)		(251.800)			(1.029)		(1.527)
Materials				0.747*	1.527*				0.338	0.27
				(0.432)	(0.841)				(0.417)	(0.854)
Survey round fixed effects	No	Yes	No	No	Yes	No	Yes	No	No	Yes
Firm fixed effects	No	Yes	No	No	Yes	No	Yes	No	No	Yes
R^2	0.151	-0.083	.	0.674	-0.921	0.21	-0.006	0.195	0.601	-0.317
N	3135	3134	3135	3135	3134	3133	3132	3038	3104	3008

All regressions run DMW's preferred sample. Dependent variable in columns 1-5 is real (CPI-adjusted) revenue in levels, and in columns 6-10 is real revenue in logs. Instruments in all regressions are a set of 4 dummy variables indicating grant status. Standard errors in parenthesis clustered at the firm level. ** $p < .05$ * $p < .1$

Table 7: IV Results - Profits

	Profits in Levels					Profits in Logs				
	1	2	3	4	5	6	7	8	9	10
Capital	8.259**	5.162**	8.256**	15.504	0.006	0.594**	0.310**	0.583**	0.486	-0.273
	(1.957)	(2.257)	(1.959)	(10.519)	(6.720)	(0.115)	(0.124)	(0.108)	(0.446)	(0.562)
Labor			0.739		93.333			0.341		0.944
			(40.742)		(76.178)			(0.746)		(1.190)
Materials				-0.192	0.185				0.092	0.608
				(0.269)	(0.219)				(0.415)	(0.728)
Survey round fixed effects	No	Yes	No	No	Yes	No	Yes	No	No	Yes
Firm fixed effects	No	Yes	No	No	Yes	No	Yes	No	No	Yes
R^2	0.04	-0.092	0.042	.	-1.26	0.192	-0.016	0.233	0.316	-0.818
N	3103	3102	3103	3103	3102	3103	3102	3011	3076	2983

All regressions run on DMW's preferred sample. Dependent variable in columns 1-5 is real profits in levels, and in columns 6-10 is profits in logs. Profits not adjusted for firm owner's own labor or cost of capital. Instruments in all regressions are a set of 4 dummy variables indicating grant status. Standard errors in parenthesis clustered at the firm level. ** $p < .05$ * $p < .1$

Table 8: Univariate Structural Estimation

	Profits in levels			Profits in logs			Revenue in levels			Revenue in logs		
	1	2	3	4	5	6	7	8	9	10	11	12
						Full Sample						
Capital	3.682**	3.980**	4.207**	0.396**	0.413**	0.402**	27.109**	30.397**	29.065**	0.561**	0.598**	0.578**
	(0.836)	(0.786)	(0.726)	(0.039)	(0.041)	(0.038)	(5.064)	(3.912)	(3.767)	(0.065)	(0.060)	(0.054)
N	3032	2401	2951	3028	2401	2943	3061	2410	2977	3056	2410	2969
						Control firms						
Capital	3.649**	4.931**	5.175**	0.367**	0.394**	0.373**	30.830**	31.270**	0.476**	0.547**	0.482**	48.245**
	(1.015)	(0.953)	(0.866)	(0.039)	(0.044)	(0.039)	(4.525)	(4.593)	(5.033)	(0.061)	(0.061)	(0.055)
N	1649	1141	1607	1648	1141	1605	1669	1142	1626	1668	1142	1624
						Treatment firms						
Capital	4.077**	3.877**	4.007**	0.434**	0.434**	0.438**	14.690**	28.950	28.629**	0.634**	0.645**	0.643**
	(1.050)	(0.883)	(0.771)	(0.057)	(0.048)	(0.044)	(9.578)	(4.510)	(5.187)	(0.107)	(0.067)	(0.062)
N	1383	1260	1344	1380	1260	1338	1392	1268	1351	1388	1268	1345
Proxy	Materials and inventories	Fraction of materials used	Owner's labor	Materials and inventories	Fraction of materials used	Owner's labor	Materials and inventories	Fraction of materials used	Owner's labor	Materials and inventories	Fraction of materials used	Owner's labor

Dependent variable in columns 1-3 is profits in levels, in columns 4-6 is profits in logs, in columns 7-9 is revenue in levels, and in columns 10-12 is revenue in logs. Standard errors in parenthesis clustered at the firm level. ** p < .05 * p < .1

Figures

Figure 1: Productivity as a Function of Capital, and Materials and Inventories

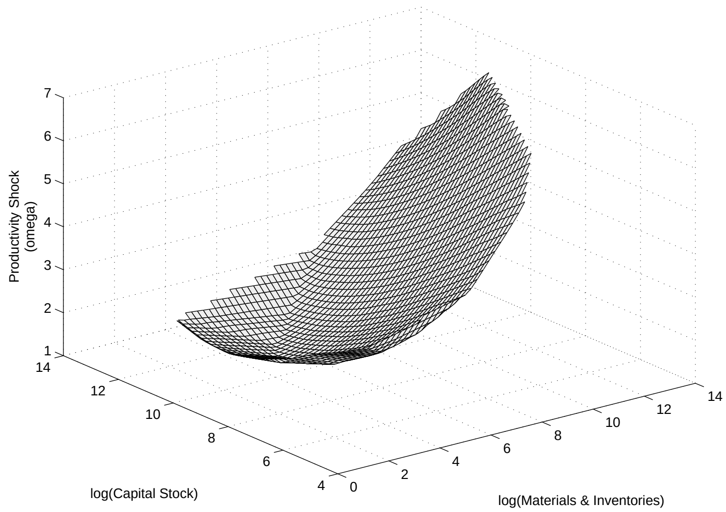

Table 10: Structural Estimation of Production Functions

	Revenue in Logs			
	Levinsohn & Petrin estimator		Ackerberg, Caves, & Frazer estimator	
	1	2	3	4
Log capital	0.148**	0.111*	0.146**	0.098
	(0.038)	(0.055)	(0.044)	(0.064)
Log materials and inventories	0.566**	0.007	0.579**	0.018
	(0.058)	(0.112)	(0.087)	(0.154)
Log total labor	0.170**	-0.164	0.277	-0.120
	(0.033)	(0.194)	(0.225)	(0.211)
Log owner's age		0.157*		0.139
		(0.072)		(0.113)
Log owner's education		0.655**		0.647**
		(0.090)		(0.186)
Female		-0.136**		-0.274
		(0.047)		(0.805)
N	2965	2896	2965	2896

Dependent variable is real revenues in logs. Standard errors in parenthesis clustered at the firm level. ** p < .05 * p < .1

Table 11: Production Function Parameters by Sector

	Revenue in logs		
	Manufacturing	Services	Trade
	1	2	3
Log capital	0.142**	0.065	0.160
	(0.057)	(0.461)	(0.100)
Log materials and inventories	0.528**	0.910	0.543**
	(0.094)	(1.831)	(0.182)
Log total labor	0.212**	0.280**	0.049
	(0.039)	(0.063)	(0.053)
N	1261	444	1260

Dependent variable is real revenues in logs. Standard errors in parenthesis clustered at the firm level. ** p < .05 * p < .1

Figure 2: Productivity as a Function of Capital, and Fraction Materials and Inventories Used

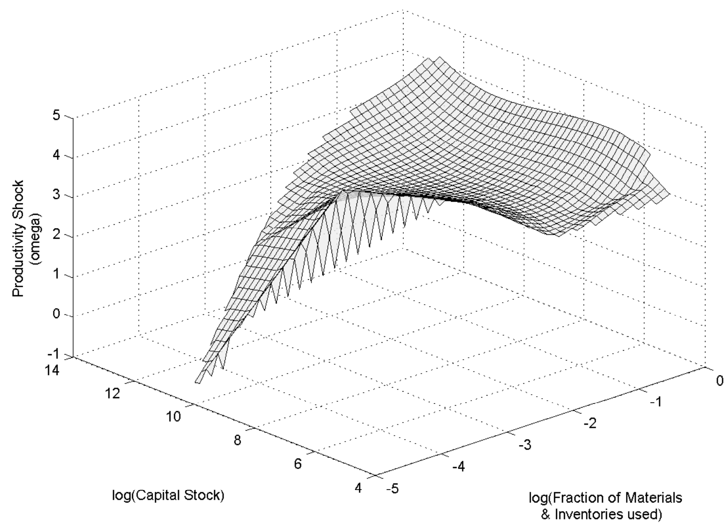

Figure 3: Productivity as a Function of Capital, and Hours of Owner Labor