Labor and Capital Misallocation across Firms: Evidence from Ethiopia Manufacturing Sectors*

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Måns Söderbom[1]
University of Gothenburg
Sweden

Hailegebriel Yigezu[2]
Addis Ababa University
Ethiopia

Abstract

We develop a framework for analyzing capital and labor misallocation across firms and estimate the parameters of the model using plant-level from Large and Medium Scale Industries in Ethiopia. We show that the dispersion in the average revenue product of capital and labor across firms is much higher in Ethiopia than in high and middle-income countries as documented in previous studies. This result, which remains robust to controls for productivity measurement errors, suggests that capital and labor are severely misallocated across Ethiopian firms. We show that (log) aggregate TFP can be written as a linear function of the variances of the revenue product of capital and labor and their covariance, and report results indicating that the cost of misallocated labor, in terms of foregone aggregate TFP, is greater than that of misallocated capital. Distinguishing different sources of capital and labor misallocation, our empirical results indicate that distortions that lead to a positive correlation between labor costs and productivity are quantitatively the most important driving factor of the negative effects of resource misallocation on aggregate TFP. The result that high productivity tends to be accompanied by high labor costs remains robust when controlling for heterogeneity in skills across firms and implies muted incentives for firms to grow in response to positive productivity and demand shocks. Policy measures effective at reducing labor market distortions may thus have large positive effects on aggregate TFP and aggregate output in low-income countries.

JEL classification: D24, E22, O11, O47

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(1) Contact: mans.soderbom@economics.gu.se.
(2) Contact: hailaenani@gmail.com.

1. Introduction

It is now widely recognized that the misallocation of resources, such as physical capital, labour, and talent, constrains economic development in low-income countries. In this paper, we analyze the dispersion in the returns on physical capital across manufacturing firms in Ethiopia. We find that the returns on capital vary much more considerably across Ethiopian firms than what has been documented for several high and middle-income countries.

There is a substantial body of research on capital misallocation within firms. Hsieh and Klenow (2009; henceforth HK) and Restuccia and Rogerson (2008, 2013) are seminal papers. Using firm-level manufacturing data from China, India, and the United States, these studies shoIt is now widely recognized that the misallocation of resources, such as physical capital, labour, and talent, constrains economic development in low-income countries. In this paper, we analyze the dispersion in the returns on physical capital across manufacturing firms in Ethiopia. We find that the returns on capital vary much more considerably across Ethiopian firms than what has been documented for several high and middle-income countries. This simple empirical fact suggests that capital is severely misallocated across firms and that the cost, in terms of lost potential output, is high. Why do returns on physical capital vary so much? How large are the potential gains from mitigating capital misallocation across firms? And to what extent do measurement errors in the data pose a threat to the credibility of research on capital misallocation? These are the key research questions in this paper.

Kumari et al. (2021) show that misallocation is a mechanism underlying the slowing growth of many emerging economies. Using a firm-level dataset from Sri Lanka's manufacturing surveys and a standard model of misallocation, they demonstrated that eliminating misallocation could boost aggregate manufacturing productivity by 102% between 1994 and 2015. Inklaar et al. (2017) discover that resource misallocation has a negative impact on manufacturing productivity levels using data from the World Bank Enterprise Survey on formal manufacturing firms in 52 low and middle-income countries. Fossati et al. (2021) examine the extent and potential determinants of resource misallocation in Latin America and Africa using cross-sectional data from the World Bank Enterprise Survey from various years (WBES).

Adopting the HK methodology, their findings show that the extent of resource misallocation is greater in Africa than in Latin America. These authors also identify international trade barriers as a major source of resource misallocation and emphasis the importance of reducing friction in international trade. Kalemli-Ozcan and Sørensen (2014) analyze the World Bank Enterprise Survey data through the HK lens and find that the strength of property rights and the quality of the legal system help explain country-level differences in capital misallocation. Using the HK methodology, they discovered that the extent of resource misallocation in Africa is greater than in Latin America. These authors also identified international trade barriers as a major source of resource misallocation, emphasizing the importance of reducing friction in international trade. Through the HK lens, Newman et al. (2019) examine World Bank Enterprise Survey data and discover that the strength of property rights and the quality of the legal system help explain country-level differences in capital misallocation. w that resource misallocation across firms within a sector can have a significant impact on aggregate manufacturing TFP. Several studies have used the Hong Kong approach to investigate capital misallocation in other regions.

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Bun and Winter (2022) used firm-level panel data from 2001 to 2017 to investigate capital and labour misallocation in the Netherlands. They used the dispersion in marginal revenue products of capital and marginal revenue products of labour to determine the extent of capital and labour misallocation. They concluded that misallocation had a significant negative impact on aggregate productivity and that capital misallocation, in particular, has increased over time and is far more permanent than labour misallocation.

[1] The HK framework has been used for studies of resource allocation in sectors other than manufacturing. We largely abstract from this line of work here. However, the work of Chen et al. (2022) on Ethiopia is of some relevance. These authors analyze the effects of land markets on resource allocation and agricultural productivity using household-level panel data from the World Bank, the Ethiopia Integrated Survey of Agriculture (ISA), for waves 2013/14 and 2015/16. They assess the effect of land certification on resource misallocation and productivity using a difference-in-differences approach and found that certification facilitates rentals and improves agricultural productivity.

Some recent studies take a more structural approach to identify the causes of capital misallocation and quantifying the economic consequences. Asker et al. (2014) look at how dynamic production inputs and adjustment costs shape the dispersion of static measures of capital misallocation across industries and countries. Asker et al. analyze data from the World Bank Enterprise survey for 33 developing countries and use large-scale country-level data sets for the United States, Chile, France, India, Mexico, Romania, Slovenia, and Spain. They attribute variation in the dispersion of the marginal revenue product of capital across industries and countries to variation in the volatility of productivity using a dynamic investment model in which capital adjustment is costly.

David and Venkateswaran (2019; henceforth DV) propose a dynamic investment model with adjustment costs and uncertainty, as well as an explicit link between firm-specific market distortions and the user cost of capital. An empirical methodology for estimating the model's structural parameters is linked to their theoretical model. This methodology entails focusing on a small number of data points. The variance of the average revenue productivity of capital, which is a common measure of the dispersion in the (marginal) return on capital in the literature, is one of the moments to be fitted. DV apply their methodology to data on Chinese and American manufacturing firms. They discover that firm-specific distortions attributed to economic policies or institutional features explain the majority of the variation in average capital productivity in the data. Adjustment costs also contribute to greater dispersion, but their economic significance is generally minor. David et al. (2021) extend the DV methodology to include data from more countries, including some developing countries.

They discover that adjustment costs account for only a small portion of the observed dispersion in capital productivity. The main source of capital misallocation is found to be market distortions that cause variation in the effective user cost of capital. Kilumelume et al. (2021)

examine the impact of tariffs on capital allocation using South African CIT data and the DV methodology. Their empirical findings show that tariffs exacerbate capital misallocation and reduce aggregate productivity.

A few studies have looked into capital misallocation in Sub-Saharan Africa (SSA). Cirera et al. (2020) investigate the extent, costs, and nature of within-industry resource misallocation in Côte d'Ivoire, Ethiopia, Ghana, and Kenya's manufacturing sectors.[2] Using the HK methodology, the authors discover that resources are severely misallocated in all of the countries studied, and that distortions are positively related to firm-level productivity. The latter result demonstrates that more productive ("good") firms are "taxed" more heavily. Gebresilasse (2019) investigated whether industrial policy caused resource misallocation across firms in Ethiopia's manufacturing sector. Gebresilasse reports findings indicating that the so-called priority sector support policy exacerbates the extent of misallocation and has a negative impact on firms' physical and revenue productivity using the HK methodology and a difference-in-differences approach. He concludes that the elimination of sector-specific distortionary policies contributed to increases in allocative efficiency.

While the importance of the studies based on the HK methodology is undisputable, the framework does have some limitations. The most obvious example is the abstraction of dynamic mechanisms. The empirical analysis is theoretically based on a set of static first-order conditions for optimal input (e.g., capital) levels. If the firm encounters "frictions," such as adjustment costs, the static first-order conditions no longer apply. Thus, David and Venkateswaran (2019) make an important contribution that allows this shortcoming to be addressed. Another set of issues, not unrecognized but likely under-recognized in the literature, is related to data quality. Remember that empirical measures of dispersion, such as the sample variance in the (log of)

[2] National Treasury and UNU-WIDER (2019a, 2021).

revenue-to-capital ratio, are commonly used in analyses of capital misallocation. If revenues and/or capital are measured incorrectly, empirical measures of dispersion may overestimate true dispersion, exaggerating the extent of capital misallocation. Bils et al. (2021) propose a method for determining how much measurement errors inflate average product dispersion. Their method exploits when a plant's average products are overstated due to measurement error, revenue growth is less sensitive to input growth. Using Indian manufacturing from 1985 to 2013, their correction reduces potential reallocation gains. DV employs the proposed test by Bils et al and discovers that their empirical results for the United States and China are robust to measurement errors. While this is reassuring, it may not apply to data collected by resource-constrained statistical agencies or survey teams in low-income countries.

The rest of the paper is organized as follows: Section 2 provides a theoretical framework and methodology. Section 3 presents the data. Section 4 presents empirical results for moments and structural parameters. Section 5 summarizes and concludes.

2. Conceptual Framework

In this section, we develop a theoretical model that enables us to analyze the demand for capital and labor. To facilitate comparisons with previous research on high- and middle-income countries, we take the dynamic investment model developed by David and Venkateswaran (2019) as our point of departure. Key assumptions include: there is a continuum of firms producing intermediate goods by means of a two-factor (labour and capital) Cobb-Douglas production function with non-increasing returns to scale; these intermediate goods are used as inputs for the production of a single final good through a constant elasticity of substitution (CES) aggregator; firm-level productivity follows an AR(1) process in logs; labor becomes productive instantaneously on hiring the worker; capital becomes productive with a one-period lag ('time-to-build'); investment is subject to quadratic capital adjustment costs; hiring workers is subject to quadratic labor adjustment costs; market distortions imply that the effective costs of capital and labor are heterogenous over time and across firms; at time period t, the firm receives a 'signal' of productivity in period t+1; and, firms choose labor and capital in order to maximize the value of the firm. Under these assumptions, the firm's problem in a stationary equilibrium can be written as

$$
\begin{aligned}
V\left(K_{t+1}, L_t; K_t, L_{t-1}\right) \quad = \quad & \max_{K_{t+1}, L_t} E_t[\Pi\left(K_t, L_t; \hat{A}_t\right) - T_t^L W L_t - T_{t+1}^K K_{t+1}\left(1-\beta\left(1-\delta\right)\right) \\
& -\Phi\left(K_{t+1}, K_t\right) - \Lambda\left(L_t, L_{t-1}\right) + \beta V\left(K_{t+2}, L_{t+1}; K_{t+1}, L_t\right)],
\end{aligned}
$$

where V_t is firm value, K_t is physical capital, L_t is labor, W is the wage rate, β is the discount rate, δ is the capital depreciation rate, $\Pi\left(K_t, L_t; \hat{A}_t\right) = Y^{\frac{1}{\omega}} \hat{A}_t K_t^{\alpha_1} L_t^{\alpha_2}$ is the revenue function, $\alpha_j = \hat{\alpha}_j\left(1-\frac{1}{\theta}\right)$, where $\hat{\alpha}_j$ denotes the parameter associated with input j in a Cobb-Douglas production function, θ is interpretable as the price elasticity of demand, and T_t^L and T_{t+1}^K are "wedge" parameters which shift the unit prices of labor, and capital, respectively. Finally, $\Phi\left(K_{t+1}, K_t\right)$ is s capital adjustment cost function, and $\Lambda\left(L_t, L_{t-1}\right)$ is a labor adjustment cost function, both of which are assumed quadratic and symmetric:

$$
\Phi\left(K_{t+1}, K_t\right) = \frac{\hat{\xi}}{2}\left(\frac{K_{t+1}}{K_t} - (1-\delta)\right)^2 K_{it}, \tag{2.1}
$$

$$
\Lambda\left(L_t, K_{t-1}\right) = \frac{\hat{\lambda}}{2}\left(\frac{L_t}{L_{t-1}} - (1-q)\right)^2 L_{i,t-1}. \tag{2.2}
$$

The law of motion for capital is $K_{t+1} = I_t + (1-\delta) K_t$,where I is investment (new purchases). For labor, $L_t = H_t + (1-q) L_{t-1}$where H_t is new hires and q is the quit rate. Note that new hires (H) become productive instantaneously, while new investments become productive with a one-period lag ("time-to-build").

The first-order conditions for K_{t+1} and L_t can be written as Euler equations[3]:

$$-T^K_{t+1}\left(1-\beta\left(1-\delta\right)\right)-\Phi_1\left(K_{t+1},K_t\right)=\beta E_t[\Pi_{K,t+1}-\Phi_2\left(K_{t+2},K_{t+1}\right)], \tag{2.3}$$

$$\Pi_{L,t}\left(K_t,L_t;\hat{A}_t\right)-T^L_tW-\Lambda_1\left(L_t,L_{t-1}\right)=\beta E_t\left[\Lambda_2\left(L_{t+1},L_t\right)\right]. \tag{2.4}$$

Log-linearizing around the undistorted non-stochastic steady state, we can express the Euler equation for capital as

$$k_{t+1}\left(\left(1+\beta\right)\xi+1-\alpha_1\right)=E_t\left(\hat{a}_{t+1}+\tilde{\tau}^K_{t+1}\right)+\beta\xi E_t\left(k_{t+2}\right)+\xi k_t+\alpha_2E_t\left(l_{t+1}\right) \tag{2.5}$$

where

$$\tilde{\tau}^K_{t+1}=\frac{-\left(1-\beta\left(1-\delta\right)\right)}{1-\beta\left(1-\delta\right)+\hat{\xi}\delta\left(1-\beta\left(1-\frac{\delta}{2}\right)\right)}\log T^K_{t+1} \tag{2.6}$$

captures capital market distortions,

$$\xi=\frac{\hat{\xi}}{1-\beta\left(1-\delta\right)+\hat{\xi}\delta\left(1-\beta\left(1-\frac{\delta}{2}\right)\right)} \tag{2.7}$$

reflects capital adjustment costs, and $k,\hat{a},l$ denote log capital, log productivity, and log labor, respectively.[4] The log-linearized Euler equation for labor is

$$l_t\left[\left(1+\beta\right)\lambda+1-\alpha_2\right]=\hat{a}_t+\tilde{\tau}^L_t+\lambda l_{t-1}+\alpha_1k_t+\beta\lambda E_t\left(l_{t+1}\right), \tag{2.8}$$

where

$$\tilde{\tau}^L_t=-\frac{W}{W+\hat{\lambda}q\left(1-\beta\left(1-\frac{q}{2}\right)\right)}\log T^L_t \tag{2.9}$$

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[3] Notation: We take $F_1\left(X,Y\right)$ to mean $\frac{dF(X,Y)}{dX}$, and $F_2\left(X,Y\right)$ to mean $\frac{dF(X,Y)}{dY}$.

[4] For these derivations, we use the approach proposed by David and Venkateswaran (2019), extended to allow for a dynamic labor decision of the firm. Details are provided in Appendix B (not yet available).

represents labor market distortions and

$$\lambda = \frac{\hat{\lambda}}{W + \hat{\lambda} q \left(1 - \beta \left(1 - \frac{q}{2}\right)\right)} \tag{2.10}$$

reflects labor adjustment costs.

Next, we specify the stochastic processes for productivity and distortions. Here we follow David and Venkateswaran (2019) closely. Adding firm subscripts i, we assume that log productivity can be written as the sum of a time varying component and a firm fixed effect:

$$\hat{a}_{it} = \overline{a}_i + \widetilde{a}_{it}, \qquad \overline{a}_i \sim N\left(0, \sigma^2_{\overline{a}}\right) \tag{2.11}$$

where time varying productivity follows an AR(1) process:

$$\widetilde{a}_{it} = \rho \widetilde{a}_{i,t-1} + \mu_{it}, \qquad \mu_{it} \sim N\left(0, \sigma^2_{\mu}\right) \tag{2.12}$$

where ρ is the persistence parameter and σ^2_μ is the variance of the productivity shocks.

The distortions are written as

$$\begin{aligned} \tilde{\tau}^K_{i,t+1} &= \gamma_K \widetilde{a}_{it} + \varepsilon_{i,t+1} + \chi_i, \qquad && \varepsilon_{it} \sim N\left(0, \sigma^2_\varepsilon\right), \chi_i \sim N\left(0, \sigma^2_\chi\right) && (2.13) \\ \tilde{\tau}^L_{it} &= \gamma_L \widetilde{a}_{it} + u_{it} + \theta_i, && u_{it} \sim N\left(0, \sigma^2_u\right), \theta_i \sim N\left(0, \sigma^2_\theta\right), && (2.14) \end{aligned}$$

where the parameters γ_K and γ_L determine the extent to which the costs of capital and labor, respectively, co-vary with time-varying productivity, ε_{it} and u_{it} are time varying non-autocorrelated shocks to the costs of capital and labor, respectively, and χ_i and θ_i are time-constant determinants (fixed effects) of the costs of capital and labor, respectively; and $\sigma^2_\varepsilon, \sigma^2_\chi, \sigma^2_u$ and σ^2_θ denote the variance of ε_{it}, χ_i, u_{it} and θ_i, respectively. Note that *high* values of $\tilde{\tau}^K_{i,t+1}$

and $\tilde{\tau}_{it}^{L}$ correspond to *low* costs of capital and labor, respectively; hence $\gamma_K < 0$ implies that high-productivity firms face a high cost of capital, while $\gamma_L < 0$ means that high-productivity firms face a high cost of labor.

In our model, capital becomes productivity with a lag. That is, the firm decides on K_{t+1} in period t, based on the information available at that time. However, the firm may have some information at time t about the productivity in period $t+1$, in which case this information will affect the capital decision. To formalize this idea, we follow David and Venkateswaran (2019) and assume that the firm observes at time t a 'noisy signal' $s_{i,t+1}$ of the following period's productivity shock:

$$s_{i,t+1} = \mu_{i,t+1} + e_{i,t+1}, \qquad e_{it} \sim N\left(0, \sigma_e^2\right).$$

It follows that expected productivity in $t+1$ can be written

$$E_{it}\left(\widetilde{a}_{i,t+1}\right) = \rho\widetilde{a}_{it} + \frac{V}{\sigma_e^2} s_{i,t+1}.$$

The parameter V is bounded between 0 and σ_μ^2. If $V = 0$, the firm has perfect knowledge about productivity in period $t+1$: $E_{it}\left(\widetilde{a}_{i,t+1}\right) = \rho\widetilde{a}_{it} + \mu_{i,t+1} = \widetilde{a}_{i,t+1}$. In contrast, if $V = \sigma_\mu^2$, the firm has no knowledge about productivity in period $t+1$: $E_{it}\left(\widetilde{a}_{i,t+1}\right) = \rho\widetilde{a}_{it}$. In the emprical analysis below, we estimate the ratio V/σ_μ^2, and refer to this ratio as the "noise" in the productivity signal received at t. In order to simplify the notation below, we define $\widetilde{a}_{i,t+1}^{e} = E_{it}\left(\widetilde{a}_{i,t+1}\right)$.

Using the expressions above for input market distortions, adjustment costs, and productivity - i.e. equations (2.6), (2.7), (2.9), (2.10), (2.11), and (2.12) - we can derive from the Euler equations (2.5) and (2.8) log linear decision rules for capital and labor:

$$k_{i,t+1} = \psi_1 k_{it} + \psi_2 \widetilde{a}^e_{i,t+1} + \psi_3 l_{it} + \psi_6 \theta_i + \psi_7 \varepsilon_{i,t+1} + \psi_8 \chi_i + \psi_9 \overline{a}_i \tag{2.15}$$

$$l_{it} = \phi_1 l_{t-1} + \phi_2 \widetilde{a}_{it} + \phi_3 k_{it} + \phi_4 \widetilde{a}^e_{i,t+1} + \phi_5 u_{it} + \phi_6 \theta_i + \phi_7 \varepsilon_{i,t+1} + \phi_8 \chi_i + \phi_8 \overline{a}_i. \tag{2.16}$$

The variables on the right-hand side of these equations are interpretable as the 'state variables' that determine the 'control variables' on the left-hand side of the equations.[5] The two equations are not symmetric because of the (assumed) timing differences. For example, because capital becomes productive with a lag, the shock u_{it}, which is serially uncorrelated, affects $k_{i,t+1}$ only through its effect on l_{it}, and has no independent effect on the capital decision. In the general case, the coefficients $\psi_1, ..., \psi_8, \phi_1, ..., \phi_8$ in (2.15) and (2.16) are complicated functions of the structural parameters of the model.[6] Appendix Table 1 provides some illustrations of the connections between the structural parameters and the decision rule coefficients.[7]

2.1. Aggregate Implications of Misallocation

Based on a model in which capital decisions are affected by adjustment costs and capital market distortions, and labor is a flexible input that can be hired instantaneously by firms in a non-distored labor market at zero adjustment cost, David and Venkateswaran (2019) derive the

[5] The decision rule for capital (2.15) contains the capital misallocation model derived by David and Venkateswaran (2019) as a special case. Specifically, we obtain their model if $\lambda = \gamma_L = \sigma^2_u = \sigma^2_\theta = \sigma^2_{\overline{a}} = 0$, so that labor is a fully flexible input, the labor market is free from distortions, and there are no productivity fixed effects. In this case, $k_{i,t+1}$ will vary with $k_{it}, \widetilde{a}^e_{i,t+1}, \varepsilon_{i,t+1}, \chi_i$ only.

[6] We use Mathematica to obtain the equations determining these relationships.

[7] The first column of Appendix Table A1 illustrates the case in which there are no adjustment costs or distortions. In this case the first-order conditions for capital and labor are not dynamic, which makes it straightforward to derive the coefficients of the decision rules. Lags of capital and labor are irrelevant for the current decisions on capital and labor in such a setting. The second column shows the effects of adding (relatively high) capital adjustment costs. Such adjustment costs imply that optimal capital depend on lagged capital, and is less responsive to productivity changes than under no adjustment costs. The firm becomes less responsive to factor prices changes than under no adjustment costs. Columns 3 and 4 of the table shows how the decision rule parameters change when we add labor adjustment costs. Introducing correlated distortions implies that the coefficients on current and expected future productivity become smaller, see col. (5) in the table. This is because the correlated distortions imply that a positive productivity shock is associated with higher costs of capital and labor.

following expression for aggregate output y:

$$y = a + \hat{\alpha}_1 k + \hat{\alpha}_2 n,$$

where k and n are log aggregate capital and labor, respectively, and a is aggregate TFP:

$$a = a^* - \frac{(\theta\widehat{\alpha}_1 + \widehat{\alpha}_2)\,\widehat{\alpha}_1}{2}\sigma^2_{arpk}, \tag{2.17}$$

where a^* is a constant. Equation (2.17) shows that an increase in the dispersion of *arpk* decreases aggregate TFP. Hence, if we can identify the sources of dispersion in *arpk*, it is possible to quantify their respective effects on aggregate TFP using eq. (2.17)

If there are labor market distortions, then the formula above for aggregate TFP no longer applies. We thus require a generalized expression for aggregate TFP that holds under the joint misallocation of capital and labor. We show in Appendix D that the generalized expression is given by

$$a = a^* - \frac{1}{2}\left(\theta\widehat{\alpha}_1 + \widehat{\alpha}_2\right)\widehat{\alpha}_1\sigma^2_{arpk} - \frac{1}{2}\left(\theta\widehat{\alpha}_2 + \widehat{\alpha}_1\right)\widehat{\alpha}_2\sigma^2_{arpl} - (\theta - 1)\,\widehat{\alpha}_1\widehat{\alpha}_2\sigma_{arpk,arpl}, \tag{2.18}$$

where $\sigma_{arpk,arpl}$ is the covariance between *arpk* and *arpl*.[8] It can be noted that reasonable parameter values imply a considerably larger negative effect of labor misallocation than capital misallocation. For example, $\widehat{\alpha}_1 = 1/3, \widehat{\alpha}_2 = 2/3$ and $\theta = 6$ imply that the effect of labor misallocation is $\frac{da}{\sigma^2_{arpl}} = -1.44$ (plus any effect operating through the covariance term), while the effect of capital misallocation is only $\frac{da}{\sigma^2_{arpk}} = -0.44$ (plus any effect operating through the covariance term).

[8] Note that this expression coincides with the expression derived by David and Venkateswaran if $\sigma^2_{arpn} = \sigma_{arpk,arpn} = 0$, which will be the case if there are no labor market distortions in the model derived above.

3. Identification and Estimation

We focus on estimating 9 parameters that are central for misallocation, namely: the adjustment cost parameters (ξ and λ); the market distortion parameters, distinguishing the correlated factors (γ_K and γ_L), the transitory factors (σ_ε^2 and σ_u^2) and the permanent factors (σ_χ^2 and σ_θ^2); and the noise parameter V/σ_μ^2. The estimation procedure involves computing a set of moments based on the decision rules (2.15) and (2.16), which in turn depend on the structural parameters of interest, and iterating on the underlying parameter values until the moments implied by the decision rules match those of the real data. We now turn to the important issue of moment selection.

David and Venkateswaran (2019) show that, if there are no labor market distortions or labor adjustment costs, (local) identification of the capital misallocation parameters $\xi, \gamma_K, \sigma_\varepsilon^2$ and σ_χ^2 can be based on the following five moments: the correlation between investment growth and lagged productivity growth (denoted $\rho_{\Delta\iota,\Delta a_{-1}}$); the correlation between current and lagged investment growth ($\rho_{\Delta\iota,\iota\Delta_{-1}}$); the correlation between the average product of capital and productivity ($\rho_{arpk,a}$); the variance of investment growth ($\sigma_{\Delta\iota}^2$); and the variance of average product of capital (σ_{arpk}^2). Identification of the labor misallocation parameters introduced in this paper can be based on moments similar to those proposed by David and Venkateswaran, with labor (growth) taking the place of capital.

Figure 1 provides an illustration of the identification of the labor misallocation parameters. Panel A in Figure 1 shows the labor adjustment cost parameter λ on the horizontal axis, and the correlated labor distortion parameter γ_L on the vertical axis. The downward sloping curve in this graph is an 'isomoment' curve for the serial correlation in hiring growth ($\rho_{\Delta h,h\Delta_{-1}}$). It shows combinations of parameter values of λ and γ_L that yield a particular (constant) value of $\rho_{\Delta h,h\Delta_{-1}}$. The upward sloping curve in the graph is an isomoment curve for the variance of hiring growth ($\sigma^2_{\Delta h}$), thus showing combinations of parameter values of λ and γ_L that yield a constant value of $\sigma^2_{\Delta h}$. The intersection of the two isomoment curves reflects the unique combination of λ and γ_L that is consistent with the combination of values of both moments. Thus, while either moment, on its own, does not identify the adjustment cost parameter or the distortion parameter, $\rho_{\Delta h,h\Delta_{-1}}$ and $\sigma^2_{\Delta h}$ jointly identify λ and γ_L.

Panel B of Figure 1 shows that the combination of $\sigma^2_{\Delta h}$ and the correlation between hiring growth and lagged productivity growth ($\rho_{\Delta h,\Delta a_{-1}}$) identifies the variance of the transitory labor market distortions (σ^2_u). Panel C illustrates how the permanent labor market distortion parameter σ^2_θ is identified. The downward sloping curve, i.e. the isomoment curve for σ^2_{arpl}, shows that low values of σ^2_θ must be accompanied by high values of σ^2_u, for σ^2_{arpl} to remain constant. The horizontal isomoment curve for $\sigma^2_{\Delta h}$ implies that σ^2_θ does not affect $\sigma^2_{\Delta h}$, which is not surprising since θ_i is a time-constant fixed effect. Hence, for the parameter pair $\left(\sigma^2_u, \sigma^2_\theta\right)$, there is a single value of σ^2_u that matches $\sigma^2_{\Delta h}$, which in turn implies that σ^2_θ is pinned down by σ^2_{arpl}.

The moments discussed above are the core moments underlying identification and estimation of the model parameters in this paper. We add to this set a small number of additional moments. We specifically consider the serial correlation and variance of investment and hiring, denoted $\rho_{\iota,\iota_{-1}}$, σ^2_ι, $\rho_{h,h_{-1}}$, and σ^2_h, respectively. These moments are distinct from investment and hiring *growth,* which are already included in the core set of moments. Moreover, because labor is assumed to respond instantaneously to productivity (see (2.16)), we add the correlation between hiring growth and *current* productivity growth, $\rho_{\Delta h,\Delta a}$, to the set of moments. Finally, to preserve symmetry across the sets of moments related to capital and labor, we also add the correlation of investment growth and current productivity ($\rho_{\Delta\iota,\Delta a}$), and the correlation between *arpl* and productivity ($\rho_{arpk,a}$), to the set of moments. We thus have 16 moments which form the basis for the estimation of 9 parameters. The moments are listed in the upper part of Table

1, $M_1 - M_{16}$.

We pre-specify some parameters of the model as follows. We assume $\alpha_1 = (1/3)\left(1 - \frac{1}{\theta}\right)$ and $\alpha_2 = (2/3)\left(1 - \frac{1}{\theta}\right)$,where θ is interpretable as the substitution elasticity between intermediate goods for the production of the final good. We set $\theta = 6$. We assume that the discount factor is $\beta = 0.95$, that the depreciation parameter is $\delta = 0.10$, and that the labor quit rate is $q = 0.10$.

The parameters of the productivity process i.e. ρ, σ_μ^2, and $\sigma_{\overline{a}}^2$ are estimated from the data. One important challenge is posed by the (likely) presence of measurement errors in the data. We turn to this issue next.

3.1. Measurement errors and estimation of productivity parameters

As noted by several authors, measurement errors pose a potentially serious problem for the analysis of resource misallocation (see e.g. Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Gollin and Udry, 2020; and Bils, Klenow, and Ruane 2021). It seems reasonable to expect issues posed by measurement errors to be particularly important for data on firms in low-income countries. In this paper, we build on results developed by Griliches and Hausman (1986), and exploit the panel dimension in the data in an attempt to allow for transitory measurement errors in productivity. Consequently, we write observed productivity as the sum of true productivity and a measurement error:

$$\hat{a}_{it}^m = \overline{a}_i + \widetilde{a}_{it} + m_{it} \tag{3.1}$$

where m_{it} is a measurement error assume to be i.i.d., with mean zero and constant variance σ_m^2. Rewriting (3.1) in terms of observables, we obtain

$$\hat{a}_{it}^m = \rho \hat{a}_{i,t-1}^m + \overline{a}_i + \mu_{it} + m_{it} - \rho m_{i,t-1}. \tag{3.2}$$

We difference the data in order to remove the fixed effect $\overline{a}_i$, a procedure that solves one problem (the bias posed by the presence of fixed effects) but introduces a new form of bias due to the correlation between $\Delta\mu_{it}$ and the differenced lagged dependent variable $\Delta\hat{a}^m_{i,t-1}$. Moreover, the differencing potentially exacerbates the bias posed by the measurement error.

Griliches and Hausman (1986) showed that, for a non-dynamic panel data model, the bias in the OLS estimator varies depending on the order of differencing, a result that can be used to test and correct for measurement errors (under certain assumpions). In the same spirit, we can exploit the fact that the bias in the OLS estimator based on short and long differences, and the variance of the dependent differenced variable, will vary with the length of differencing. Note that $J = T - 2$ differences of varying length are available:

$$\Delta_j \hat{a}^m_{it} = \rho \Delta_j \hat{a}^m_{i,t-1} + \Delta_j \mu_{it} + \Delta_j m_{it} - \rho \Delta_j m_{i,t-1} \tag{3.3}$$

where $\Delta_j X_{it} = X_{it} - X_{i,t-j}$ for $X_{it} = \{\hat{a}^m_{it}, \mu_{it}, m_{it}\}$.Let $\hat{\rho}_{\Delta j}$ denote the OLS estimate of ρ, based on the j-differenced equation, and let $\pi_{\Delta j}$ denote the bias in the OLS estimator $\hat{\rho}_{\Delta j}$:

$$p \lim \hat{\rho}_{\Delta j} = \rho + \pi_{\Delta j}. \tag{3.4}$$

It can then be shown that

$$\pi_{\Delta j} = -\frac{1}{2} \frac{\rho^{j-1} + \left(1_{\{j=1\}} + 2\rho\right) \frac{\sigma^2_m}{\sigma^2_\mu}}{\frac{1-\rho^j}{1-\rho^2} + \frac{\sigma^2_m}{\sigma^2_\mu}}, \tag{3.5}$$

while

$$var\left(\Delta_j \hat{a}^m_{it}\right) = 2\sigma^2_\mu \left(\frac{1-\rho^j}{1-\rho^2} + \sigma^2_m\right), \tag{3.6}$$

where $1_{\{j=1\}}$ is an indicator equal to 1 if $j = 1$ and zero otherwise. Replacing $p \lim \hat{\rho}_{\Delta j}$ by the empirical counterparts, i.e. OLS estimates of the coefficient on the lagged dependent variable in AR(1) specifications of different lengths of differencing, and $var(\Delta_j \hat{a}^m_{it})$ by the empirical variance of the differenced productivity, we estimate ρ, σ^2_μ and σ^2_m by means of indirect inference. This involves searching for the values of ρ, σ^2_μ and σ^2_m that minimize the distance between the empirical moments $\hat{\rho}_{\Delta 1}$, $\hat{\rho}_{\Delta 2,...,}\hat{\rho}_{\Delta J}$, $var(\Delta_1 \hat{a}^m_{it})$, $var(\Delta_2 \hat{a}^m_{it})$, ..., $var(\Delta_J \hat{a}^m_{it})$ and their theoretical counterparts, implied by (3.4), (3.5) and (3.6). That is, combining short and long differences, we obtain a set of OLS estimates of (3.3), and treat the estimated coefficients on the lagged dependent variable, along with sample variances of the dependent variables in these regressions, as moments that form the basis for estimation of ρ, σ^2_μ and σ^2_m. Finally, we can obtain an estimate of the variance of the fixed effect $\sigma^2_{\bar{a}}$ from the levels equation (3.2), exploiting $p\lim \hat{\rho} = \rho + \pi$, where

$$\pi = \frac{(1-\rho)\,\sigma^2_{\bar{a}}/\sigma^2_\mu - \rho\sigma^2_m/\sigma^2_\mu}{\frac{1}{1-\rho^2} + \sigma^2_m/\sigma^2_\mu + \sigma^2_{\bar{a}}/\sigma^2_\mu},$$

and

$$var(\hat{a}^m_{it}) = \frac{\sigma^2_\mu}{1-\rho^2} + \sigma^2_{\bar{a}} + \sigma^2_m.$$

We thus add as additional target moments the OLS estimate of the coefficient on the lagged dependent variable in the levels equation (3.2), and the variance of the dependent variable in that regression.

Our approach fits naturally with the indirect inference approach that we use for estimating the parameters of our theoretical model of the firm, but alternative methods for addressing problems posed by measurement errors in productivity are clearly available, for example instrumental variable methods (e.g. Gollin and Udry, 2020) or the methods proposed by Bils, Klenow and Ruane (2021).

3.2. Analytical expressions for target moments

Many authors use a simulations-based approach to estimate structural parameters of dynamic factor demand models. The reason, typically, for adopting a simulations-based approach is that analytical expressions cannot be obtained for some or all target moments. Under such circumstances, numerical solutions for the variables of interest are obtained, and estimation is then based on moments computed from simulated data-sets.

While intuitively appealing, the simulations-based approach potentially has some practical disadvantages. For example, estimation procedures are often time-consuming. Further, the number of data points that can be simulated affects the precision of the estimates, and the simulated data are typically drawn from a specific statistical distribution (typically the normal distribution), which may or may not be supported by the data.

Fortunately, it turns out that we can obtain analytical expressions for all target moments used in this paper, which resolves these issues. Details on the derivation of analytical expressions for the moments are provided in Appendix C.[9]

As discussed above, we estimate the parameters of interest by means of indirect inference, which involves matching theoretical moments to their empirical counterparts. Sixteen moments form the basis for estimation of the parameters of the model of capital and labor demand. To estimate the parameters of the productivity process, including the variance of measurement errors, we use regression coefficients from first up to fifth differences, and empirical variances of the dependent variable in these regressions, plus the regression coefficent from the levels equation and the variance of productivity in levels. In total, there are thus 12 moments that form the basis for estimation of the parameters of the productivity process. Following standard practice, we use as weight matrix the inverse of the covariance matrix of all 28 moments. This procedure

[9] Appendix C is not yet available.

implies that relatively precisely estimated moments receive a greater weight than imprecisely estimated moments.

4. Data

We use the establishment level annual censes survey of Large and Medium Scale Manufacturing Industry (hereafter LMSMI) that conducted by Central Statistical Agency of Ethiopia (hereafter CSA) for the sample period 2000-2016. This dataset covers all manufacturing establishments in Ethiopia that employ at least 10 employees and use power driven machines for production. The dataset is comprehensive and contains information on firms' sales, employment, intermediate inputs, labor cost (wage and salary, benefit and bonus), book value of fixed assets and other firm characteristics. The LMSMI census survey assigns unique identification number to firms, but in recent years the survey has primarily been cross-sectional in nature. Several statisticians and economists, most of whom are based in Ethiopia, have been working on collating the data in order to create a panel, and we are grateful to many individuals for their help in putting together and accessing a dataset that we can use. The dataset for our empirical analysis (hereafter 2000-2016 sample periods) contains 8,953 firms, 25,102 firm-year observations and 11 sub sectors defined at two digits ISIC level.[10]

The main variables used in our analysis are the value of sales, the value of capital and the

[10] Currently, CSA do not appear to systematically follow establishments/firms over time. The unique firm identifiers make it possible to construct a panel dataset, but a large number of establishments enter and leave the survey. Another problem is that establishments identification numbers after 2011 are not easily matched with those before 2011. Establishment identification numbers are unique within each ISIC group and LMSM round but, not necessarily across LMSM rounds. This is the root of the problem every researcher faced when creating the LMSM panel. Several statisticians and economists in Ethiopia have been working on collating the data. The work to merge the individual dataset from 1996-2013 periods and creating a unique panel identifier was done by Abebe et al. (2018, 2022). For the 2012-2017 period, the individual dataset was merged through a separate process by a team of researchers based at the Ethiopian Development Research Institute, Oxford University and International Growth Center (IGC) in Ethiopia. The merging process largely relied on firm ISIC code, establishment number, taxpayer identification number, phone number, and establishment name. Following Diao et al. (2021), and using a panel identifier for the year 2013, the final panel spans the period 2000-2016 and is created by merging parts of the 1996-2013 panel and 2012-2017 panel.

labor cost. Following Hsieh and Klenow, (2009), the book value of fixed assets at the end of the year is used as measure of capital stock. The variable investment is constructed as the change in the log of the capital stock. Sales, labor costs and capital are expressed in real terms. Following David et al. (2021), we remove industry-by-year fixed effects in order to retain only the firm-level idiosyncratic variation in the relevant data series. Further, we trim the 3% tails of each series, and we exclude observations with excessively high variability in investment (investment rates over 100%).

5. Empirical Results

5.1. Empirical Moments and Structural Estimates

Table 1 displays our empirical moments, based on the LMSMI firm-level data. The variance of the (log of) average revenue product of capital (arpk; moment M6) is 2.2 in the .This variance is much higher than what has been found for China (0.76), the US (0.55), and a number of middle-income countries (David et al., 2021). This suggests that capital misallocation is more severe in Ethiopia than in richer countries. The variance of the (log of) average revenue product of labor (moment M14) is 1.5 in the sample . This suggests that labor is less severely misallocated than capital, although it should be noted that the dispersion of labor productivity in Ethiopia is considerably higher than the dispersion of capital productivity in China and the US and several middle-income countries studied by David et al. (2021). Overall, these simple findings suggest that resource misallocation is considerably more severe in Ethiopia than in other countries.

Another striking result for Ethiopia concerns the relationship between investment growth and lagged productivity growth. For China and the US, this correlation (moment M2) is 0.29 and 0.12, respectively (David and Venkateswaran, 2019). In contrast, for Ethiopia, it is 0.03 .This finding suggest that investment is much less responsive to productivity (or demand) shocks in Ethiopia than elsewhere. In terms of our model, this suggests that the correlated distortion parameter γ_K may be a large negative, in which case the effects of positive productivity shocks on investment are muted by a corresponding increase in the cost of capital.

We calculate productivity as $\widehat{a}_{it} = vad - (\alpha_1 k_t + \alpha_2 l_t)$, where vad is value-added. We then obtain moments M17-M28, which, as discussed above, are related to the productivity process. For Ethiopia, the serial correlation in the level of productivity is 0.52. Although these estimates may be biased by measurement errors and productivity fixed effects, they at least suggest that productivity is considerably less persistent in Ethiopia than in the US (0.93) and China (0.91).

5.2. Estimation results

We begin by estimating the model without productivity fixed effects or measurement errors. Parameter estimates are shown in Table 2. For Ethiopia, the estimate of the capital adjustment cost parameter is approximately equal to 4, while the labor adjustment cost is zero. The V/σ_μ^2 ratio is 0.65, indicating that firms receive a noisy signal regarding the level of optimal capital in the subsequent period. Both effects are statistically significant at the 5% level.

We obtain negative estimates of γ_K and γ_L implying that positive productivity shocks are accompanied by higher costs of capital and labor. With the exception of the transitory distortion of labor costs for Ethiopia, the variance parameters related to input market distortions are positive. For both inputs, the variance of the time invariant distortion exceeds that of the time varying distortion.

Results shown in the lower panel of the table indicate that our model manages to reproduce the high variances of *arpk* and *arpl* documented in the data. Appendix Table A1 shows the full set of model moments implied by the parameter estimates. Overall, the model-generated moments match the real moments quite closely.

In Table 3 we show results allowing for productivity fixed effects and measurement errors. For Ethiopia, the variance of measurement errors is estimated at 0.48, which is four times the estimated variance of productivity shocks. Such a high variance of measurement errors suggest that the dispersion in observed *arpk* and *arpl* is straightforward: simply subtract the measurement variance from $var\,(arpk)$ and $var\,(arpl)$. The resulting estimates are shown in the table. The parameter ρ is estimated at 0.92, indicating strong persistence in productivity. Similar to the results shown in Table 2, we obtain large negative estimates of γ_K and γ_L, indicating that 'correlated distortions' are economically important.

Table 4 provides an illustration of what the results in Table 3 imply for considering different labor measures-wages

6. Summary and Conclusions

Market distortions lead to substantial dispersion in the productivity of capital and labor. We find evidence of quantitatively considerable higher capital and labor misallocation in Ethiopia as compared to high- and middle-income countries. In the sample period; adjustment cost of parameter for capital is higher than adjustment cost of labor, firms face some uncertainty about the productivity innovation in the following period, a positive productivity shocks accompanied by higher costs of capital and labor and all variance parameters related to input market distortions are positive. There is also empirical evidence of measurement errors in profits and capital; and correcting for measurement errors is important. Capital measurement errors thus appear to be more of a problem in Ethiopian sample and resulted a relatively large increase in the estimated capital adjustment cost.

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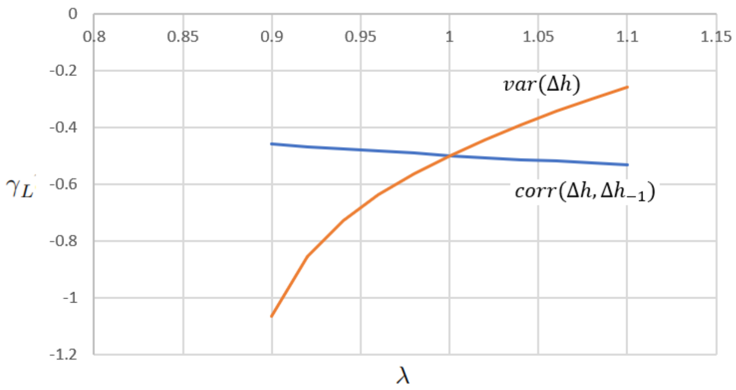
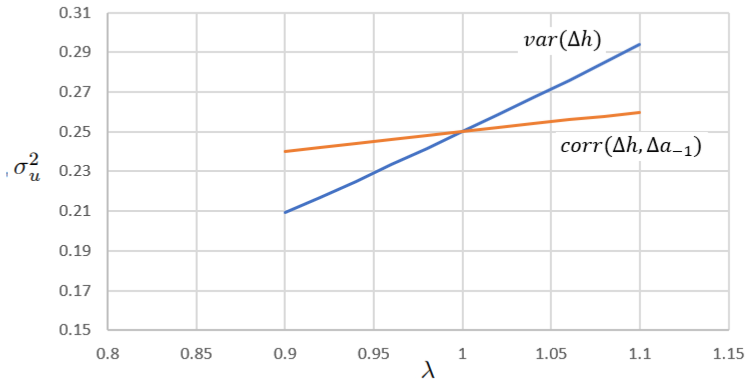
Figure 1. Pairwise identification of labor misallocation parameters

A) *Correlated labor market distortions vs. labor adjustment costs*



B) *Transitory labor market distortions vs. labor adjustment costs*



C) *Transitory vs. permanent labor market distortions*

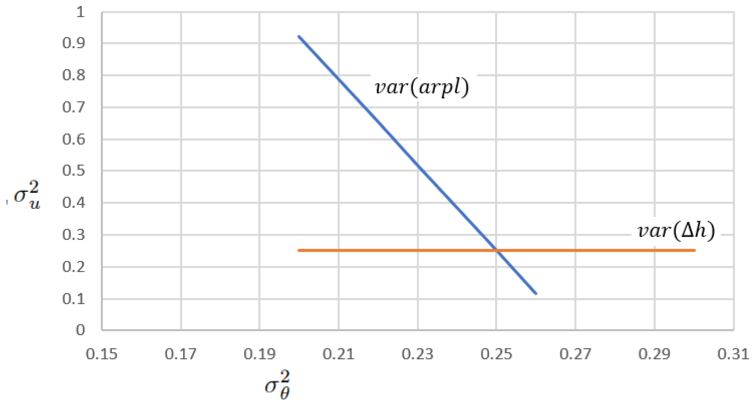


Table 1. Empirical Firm-Level Moments

	Ethiopia		Selected low,middele and high income countries[a]		
			Moment		
	Moment	St.error	Min	P50	Max
M1: $corr(\Delta i, \Delta a)$	-0.01	0.02			
M2: $corr(\Delta i, \Delta a_{-1})$	0.03	0.02	0.13	0.25	0.37
M3: $corr(\Delta i, \Delta i_{-1})$	-0.56	0.01	-0.4	-0.36	-0.29
M4: $corr(arpk, a)$	0.63	0.01	0.48	0.6	0.86
M5: $var(\Delta i)$	0.35	0.01	0.02	0.06	0.14
M6: $var(arpk)$	2.16	0.04	0.43	0.65	0.98
M7: $corr(i, i_{-1})$	-0.13	0.02	0.04	0.17	0.34
M8: $var(i)$	0.17	0.00	0.01	0.04	0.08
M9: $corr(\Delta h, \Delta a)$	-0.03	0.02			
M10: $corr(\Delta h, \Delta a_{-1})$	0.07	0.03			
M11: $corr(\Delta h, \Delta h_{-1})$	-0.58	0.01			
M12: $corr(arpl, a)$	0.93	0.00			
M13: $var(\Delta h)$	0.24	0.01			
M14: $var(arpl)$	1.45	0.03			
M15: $corr(h, h_{-1})$	-0.22	0.01			
M16: $var(h)$	0.10	0.00			
Productivity process					
M17: $\hat{r}_{Levels}$	0.52	0.01	0.89	0.93	0.98
M18: $\hat{r}_{\Delta_1}$	-0.45	0.02			
M19: $\hat{r}_{\Delta_2}$	0.11	0.02			
M20: $\hat{r}_{\Delta_3}$	0.20	0.03			
M21: $\hat{r}_{\Delta_4}$	0.23	0.03			
M22: $\hat{r}_{\Delta_5}$	0.27	0.03			
M23: $var(a_{it})$	1.18	0.03	0.24	0.59	0.92
M24: $var(\Delta_1 a_{it})$	1.11	0.06			
M25: $var(\Delta_2 a_{it})$	1.17	0.07			
M26: $var(\Delta_3 a_{it})$	1.21	0.07			
M27: $var(\Delta_4 a_{it})$	1.28	0.08			
M28: $var(\Delta_5 a_{it})$	1.32	0.08			
Observations*	15,477				
Firms	6,194				
Measure of labor	Total employment				

Note: Standard errors were obtained by means of a cluster bootstrapping procedure.
*We report the number of observations for which a complete set of observations on capital, employment and productivity are available.
[a] Source: David et al. (2021). The countries represented are: Argentina, Brazil, China, Colombia, Mexico, Malaysia, Taiwan, Thailand, Turkey, Japan and USA.

Table 2. Baseline Model: Estimated Parameters and Moments

	Parameter	coefficents	Std error
Capital adjustment cost	ξ	4.06	1.09
Noise in signal for optimal K_{t+1}	V/σ_μ^2	0.65	0.26
Correlated distortion, capital cost	γ_K	-0.60	0.11
Transitory distortion, capital cost	σ_ε^2	4.22	2.05
Permanent distortion, capital cost	σ_χ^2	1.27	0.03
Labor adjustment cost	λ	0.00	0.32
Correlated distortion, labor cost	γ_L	-1.02	0.03
Transitory distortion, labor cost	σ_u^2	0.00	0.08
Permanent distortion, labor cost	σ_θ^2	0.19	0.01
Dispersion of arpk & arpl:			
Actual: $var(arpk)$		2.16	0.04
Predicted: $var(arpk)$		2.38	0.04
Actual: $var(arpl)$		1.45	0.03
Predicted: $var(arpl)$		1.41	0.04
Capital coefficient, value-added	α_1	0.28	
Labor coefficient, value-added	α_2	0.56	
AR(1) coefficient, productivity	ρ	0.52	
Variance productivity innovation	σ_μ^2	0.86	
Productivity fixed effects?	$\sigma_{a_i}^2$	No	
Productivity measurement error?	σ_m^2	No	
Criterion value		226.8	
Measure of labor		Total employment	

Note: Standard errors are based on a bootstrapping procedure. Additional results are shown in Appendix Table A2, col. (1) and (2).

Table 3. Generalized Model Specification with Productivity Fixed Effects and Measurement Errors

	Paramete	coefficents	Std error
Capital adjustment cost	ξ	5.36	2.78
Noise in signal for optimal K_{t+1}	V/σ_{μ}^{2}	1.00	0.20
Correlated distortion, capital cost	γ_K	-0.54	0.05
Transitory distortion, capital cost	σ_{ε}^{2}	6.89	6.97
Permanent distortion, capital cost	σ_{χ}^{2}	1.30	0.03
Labor adjustment cost	λ	0.00	0.05
Correlated distortion, labor cost	γ_L	-1.06	0.04
Transitory distortion, labor cost	σ_{u}^{2}	0.00	0.01
Permanent distortion, labor cost	σ_{θ}^{2}	0.19	0.01
Dispersion of arpk & arpl:			
Actual: $var(arpk)$		2.16	0.04
Predicted: $var(arpk)$		2.23	0.04
Predicted: $var(arpk)$ no measurm't error		1.76	
Actual: $var(arpl)$		1.45	0.03
Predicted: $var(arpl)$		1.48	0.04
Predicted: $var(arpl)$ no measurm't error		1.01	
Capital coefficient, value-added	α_1	0.28	
Labor coefficient, value-added	α_2	0.56	
AR(1) coefficient, productivity	ρ	0.92	0.01
Variance productivity innovation	σ_{μ}^{2}	0.12	0.01
Productivity measurement error	σ_{m}^{2}	0.48	0.03
Productivity fixed effects	$\sigma_{a_i}^{2}$	0.00	0.01
Criterion value		121.6	
Labor measure		Total employment	

Note: Standard errors are based on a cluster bootstrapping procedure. Additional results are shown in Appendix Table A2, col. (3) and (4).

Table 4: Predicted Effects of Removing Distortions

	Δvar(*arpk*)	Δvar(*arpn*)	Δcov(*arpk*,*arpn*)	ΔlogTFP
1. No noise in signal re optimal	-0.04	0.00	-0.03	0.05
K(t+1): $V/\sigma_\mu^2 = 0$	-2%	0.00	-0.05	
2. No capital adjustment cost:	6.71	0.00	-0.10	-2.88
$\xi = 0$	382%	0%	-17%	
3. No correlated distortion of	-0.17	0.00	-0.21	0.31
capital costs: $\gamma_K = 0$	-10%	0%	-39%	
4. No transitory distortion of	-0.05	0.00	0.00	0.02
capital costs: $\sigma_\varepsilon^2 = 0$	-3%	0%	0%	
5. No permanent distortion of	-1.30	0.00	0.00	1.58
capital costs: $\sigma_\chi^2 = 0$	-74%	0%	0%	
6. No labor adjustment cost: λ=0	Not applicable (baseline estimate λ=0)			
7. No correlated distortion of	1.24	-0.81	-0.56	1.24
labor costs: $\gamma_L = 0$	71%	-80%	-101%	
8. No transitory distortion of	0.00	0.00	0.00	0.00
labor costs: $\sigma_u^2 = 0$	0%	0%	1%	
9. No permanent distortion of	0.00	-0.19	0.00	0.28
labor costs: $\sigma_\theta^2 = 0$	0%	-19%	0%	
10. Perfect signal + K distortions	-1.75	0.00	-0.56	1.40
and K adjustment cost removed	-100%	0%	-101%	
11. Perfect signal + L distortions	0.85	-1.01	-0.55	1.69
and L adjustment cost removed	48%	-100%	-100%	
12. Perfect signal + all distortions	-1.76	-1.01	-0.55	3.35
and both adjust. costs removed	-100%	-100%	-100%	

Note: Baseline values of var(*arpk*) and var(*arpl*) are obtained using the parameter estimates shown in Table 3, except that the variance of measurement errors is set to zero. The change in log TFP is calculated using the formula $\Delta TFP = -\frac{1}{2}(\theta\hat{\alpha}_1 + \hat{\alpha}_2)\hat{\alpha}_1\Delta\sigma_{arpk}^2 - \frac{1}{2}(\theta\hat{\alpha}_2 + \hat{\alpha}_1)\hat{\alpha}_2\Delta\sigma_{arpl}^2 - (\theta-1)\hat{\alpha}_1\hat{\alpha}_1\Delta\sigma_{arpk,arpl}$, where $\hat{\alpha}_1 = 1/3$, $\hat{\alpha}_2 = 2/3$, $\theta = 6$.

Table 6. Human Capital Proxied by Firm-Level Wage Bill

	Parameter	coefficents	Std error
Capital adjustment cost	ξ	0.30	0.26
Noise in signal for optimal K_{t+1}	V/σ_{μ}^{2}	0.00	0.07
Correlated distortion, capital cost	γ_K	-1.35	0.03
Transitory distortion, capital cost	σ_{ε}^{2}	0.07	0.10
Permanent distortion, capital cost	σ_{χ}^{2}	1.00	0.03
Labor adjustment cost	λ	0.11	0.07
Correlated distortion, labor cost	γ_L	-1.14	0.02
Transitory distortion, labor cost	σ_{u}^{2}	0.03	0.02
Permanent distortion, labor cost	σ_{θ}^{2}	0.15	0.02
Dispersion of arpk & arpl			
Actual: $var(arpk)$		2.16	0.04
Predicted: $var(arpk)$		2.21	0.04
Predicted: $var(arpk)$ no measurm't error		1.73	
Actual: $var(arpl)$		1.11	0.02
Predicted: $var(arpl)$		1.15	0.02
Predicted: $var(arpl)$ no measurm't error		0.67	
Capital coefficient, value-added	α_1	0.28	
Labor coefficient, value-added	α_2	0.56	
AR(1) coefficient, productivity	ρ	0.90	0.02
Variance productivity innovation	σ_{μ}^{2}	0.08	0.02
Productivity measurement error	σ_{m}^{2}	0.48	0.02
Productivity fixed effects	$\sigma_{a_i}^{2}$	0.05	0.02
Criterion value		115.8	
Labor measure		Total wage cost	

Note: Standard errors are based on a cluster bootstrapping procedure. Additional results are shown in Appendix Table A4, col. (2)-(3).

Appendix Table A1. Connections between Structural Parameters and Decision Rule Coefficients: Some Examples

Coefficients of the decision rules	1. No capital adjustment costs; no labor adjustment costs; no distortions(1)	2. High capital adjustment costs; no labor adjustment costs; no distortions(2)	3. No capital adjustment costs; very high labor adjustment costs; no distortions(3)	4. Moderate capital adjustment costs; moderate labor adjustment costs; no distortions(4)	5. Moderate capital adjustment costs; moderate labor adjustment costs; correlated distortions for capital and labor costs(5)
ψ_1	0	0.84	0	0.48	0.48
ψ_2	$(1-\alpha_1-\alpha_2)^{-1}=6$	0.53	1.67	1.41	0.70
ψ_3	0	0	0.675	0.20	0.20
ψ_6	$-\alpha_2(1-\alpha_1-\alpha_2)^{-1}=3.33$	0.53	0.41	0.87	0.87
ψ_7	$-(1-\alpha_2)(1-\alpha_1-\alpha_2)^{-1}=2.67$	0.08	1.14	0.48	0.48
ψ_8	$-(1-\alpha_2)(1-\alpha_1-\alpha_2)^{-1}=2.67$	0.42	1.54	1.05	1.05
ϕ_1	0	0	0.86	0.54	0.54
ϕ_2	$(1-\alpha_2)^{-1}=2.25$	2.25	0.09	0.54	0.27
ϕ_3	$\alpha_1(1-\alpha_2)^{-1}=0.625$	0.625	0.02	0.20	0.20
ϕ_4	0	0	0.30	0.73	0.36
ϕ_5	$(1-\alpha_2)^{-1}=2.25$	2.25	0.09	0.54	0.54
ϕ_6	$(1-\alpha_2)^{-1}=2.25$	2.25	0.52	1.31	1.31
ϕ_7	0	0	0.03	0.05	0.05
ϕ_8	0	0	0.17	0.22	0.22

(1) $\xi=0, V/\sigma_\mu^2=0, \gamma_K=0, \sigma_\varepsilon^2=0, \sigma_\chi^2=0, \lambda=0, \gamma_L=0, \sigma_u^2=0, \sigma_\theta^2=0, \alpha_1=.28, \alpha_2=.56, \rho=.8, \sigma_\mu^2=.1, \sigma_{a_i}^2=0.$

(2) $\xi=10, V/\sigma_\mu^2=0, \gamma_K=0, \sigma_\varepsilon^2=0, \sigma_\chi^2=0, \lambda=0, \gamma_L=0, \sigma_u^2=0, \sigma_\theta^2=0, \alpha_1=.28, \alpha_2=.56, \rho=.8, \sigma_\mu^2=.1, \sigma_{a_i}^2=0.$

(3) $\xi=0, V/\sigma_\mu^2=0, \gamma_K=0, \sigma_\varepsilon^2=0, \sigma_\chi^2=0, \lambda=10, \gamma_L=0, \sigma_u^2=0, \sigma_\theta^2=0, \alpha_1=.28, \alpha_2=.56, \rho=.8, \sigma_\mu^2=.1, \sigma_{a_i}^2=0.$

(4) $\xi=1, V/\sigma_\mu^2=0, \gamma_K=0, \sigma_\varepsilon^2=0, \sigma_\chi^2=0, \lambda=1, \gamma_L=0, \sigma_u^2=0, \sigma_\theta^2=0, \alpha_1=.28, \alpha_2=.56, \rho=.8, \sigma_\mu^2=.1, \sigma_{a_i}^2=0.$

(5) $\xi=1, V/\sigma_\mu^2=0, \gamma_K=-0.5, \sigma_\varepsilon^2=0, \sigma_\chi^2=0, \lambda=1, \gamma_L=-0.5, \sigma_u^2=0, \sigma_\theta^2=0, \alpha_1=.28, \alpha_2=.56, \rho=.8, \sigma_\mu^2=.1, \sigma_{a_i}^2=0.$

Note: The decision rules for labor and capital are as follows:

$$
\begin{aligned}
k_{i,t+1} &= \psi_1 k_{it} + \psi_2 \widetilde{a}^e_{i,t+1} + \psi_3 l_{it} + \psi_6 \theta_i + \psi_7 \varepsilon_{i,t+1} + \psi_8 \chi_i + \psi_9 \overline{a}_i \\
l_{it} &= \phi_1 l_{t-1} + \phi_2 \widetilde{a}_{it} + \phi_3 k_{it} + \phi_4 \widetilde{a}^e_{i,t+1} + \phi_5 u_{it} + \phi_6 \theta_i + \phi_7 \varepsilon_{i,t+1} + \phi_8 \chi_i + \phi_8 \overline{a}_i
\end{aligned}
$$

Appendix Table A2.
Estimation Results for Baseline Model: Moments and Decision Rule Parameters

	Additional results for baseline model (main results in Table 2)		Additional results for generalized model (main results in Table 3)	
	Est.	s.e.	Est.	s.e.
M1: $corr(\Delta i, \Delta a)$	0.06	0.02	0.00	0.01
M2: $corr(\Delta i, \Delta a_{-1})$	0.05	0.04	0.03	0.02
M3: $corr(\Delta i, \Delta i_{-1})$	-0.51	0.01	-0.51	0.01
M4: $corr(arpk, a)$	0.66	0.01	0.61	0.01
M5: $var(\Delta i)$	0.38	0.01	0.37	0.01
M6: $var(arpk)$	2.38	0.04	2.23	0.04
M7: $corr(i, i_{-1})$	-0.10	0.02	-0.08	0.03
M8: $var(i)$	0.17	0.00	0.17	0.00
M9: $corr(\Delta h, \Delta a)$	-0.04	0.02	-0.03	0.02
M10: $corr(\Delta h, \Delta a_{-1})$	0.12	0.02	0.06	0.01
M11: $corr(\Delta h, \Delta h_{-1})$	-0.57	0.02	-0.57	0.01
M12: $corr(arpl, a)$	0.93	0.00	0.93	0.00
M13: $var(\Delta h)$	0.26	0.01	0.25	0.00
M14: $var(arpl)$	1.41	0.04	1.48	0.04
M15: $corr(h, h_{-1})$	-0.25	0.04	-0.22	0.01
M16: $var(h)$	0.10	0.00	0.10	0.00
M17: $\hat{r}_{Levels}$			0.55	0.01
M18: $\hat{r}_{\Delta_1}$			-0.45	0.01
M19: $\hat{r}_{\Delta_2}$			0.09	0.01
M20: $\hat{r}_{\Delta_3}$			0.16	0.02
M21: $\hat{r}_{\Delta_4}$			0.22	0.02
M22: $\hat{r}_{\Delta_5}$			0.27	0.02
M23: $var(a_{it})$			1.20	0.03
M24: $var(\Delta_1 a_{it})$			1.07	0.04
M25: $var(\Delta_2 a_{it})$			1.19	0.04
M26: $var(\Delta_3 a_{it})$			1.29	0.04
M27: $var(\Delta_4 a_{it})$			1.38	0.04
M28: $var(\Delta_5 a_{it})$			1.47	0.04
Decision rule $k_{i,t+1}$				
ψ_1 (k_{it})	0.75	0.04	0.78	0.17
ψ_2 $(E_t(\tilde{a}_{i,t+1}))$	0.11	0.04	0.18	0.21
ψ_3 (l_{it})	0.00	0.04	0.00	0.02
ψ_6 (θ_i)	0.82	0.12	0.72	0.55
ψ_7 $(\varepsilon_{i,t+1})$	0.19	0.05	0.15	0.42
ψ_8 (χ_i)	0.66	0.09	0.57	0.45
ψ_9 $(\bar{a}_i)$				

The table continues on the next page.

Appendix Table A2 (cont'd)

	Additional results for baseline model (main results in Table 2)		Additional results for generalized model (main results in Table 3)	
	Est.	s.e.	Est.	s.e.
Decision rule l_{it}				
ϕ_1 ($l_{i,t-1}$)	0.00	0.21	0.00	0.06
ϕ_2 ($\tilde{a}_{it}$)	-0.03	0.01	-0.13	0.08
ϕ_3 (k_{it})	0.63	0.16	0.63	0.05
ϕ_4 ($E_t\left(\tilde{a}_{i,t+1}\right)$	0.00	0.01	0.00	0.01
ϕ_5 (u_{it})	2.25	0.72	2.25	0.24
ϕ_6 (θ_i)	2.25	0.39	2.25	0.09
ϕ_7 ($\varepsilon_{i,t+1}$)	0.00	0.01	0.00	0.02
ϕ_8 (χ_i)	0.00	0.07	0.00	0.04
ϕ_9 ($\bar{a}_i$)				

Note: Standard errors are based on a cluster bootstrap procedure.

Appendix Table A3. Firm-Level Moments based on Alternative Measures of Labor

	Moment	Std. error
Capital & labor demand		
M_1: $corr(\Delta i, \Delta a)$	-0.04	0.02
M_2: $corr(\Delta i, \Delta a_{-1})$	0.05	0.02
M_3: $corr(\Delta i, \Delta i_{-1})$	-0.56	0.01
M_4: $corr(arpk, a)$	0.70	0.01
M_5: $var(\Delta i)$	0.35	0.01
M_6: $var(arpk)$	2.16	0.04
M_7: $corr(i, i_{-1})$	-0.13	0.02
M_8: $var(i)$	0.17	0.00
M_9: $corr(\Delta h, \Delta a)$	-0.06	0.02
M_{10}: $corr(\Delta h, \Delta a_{-1})$	0.09	0.03
M_{11}: $corr(\Delta h, \Delta h_{-1})$	-0.56	0.01
M_{12}: $corr(arpl, a)$	0.89	0.00
M_{13}: $var(\Delta h)$	0.36	0.01
M_{14}: $var(arpl)$	1.11	0.02
M_{15}: $corr(h, h_{-1})$	-0.18	0.01
M_{16}: $var(h)$	0.16	0.00
Productivity process		
M_{17}: $\hat{r}_{Levels}$	0.42	0.01
M_{18}: $\hat{r}_{\Delta_1}$	-0.46	0.02
M_{19}: $\hat{r}_{\Delta_2}$	0.09	0.02
M_{20}: $\hat{r}_{\Delta_3}$	0.16	0.02
M_{21}: $\hat{r}_{\Delta_4}$	0.19	0.03
M_{22}: $\hat{r}_{\Delta_5}$	0.23	0.03
M_{23}: $var(a_{it})$	0.96	0.03
M_{24}: $var(\Delta_1 a_{it})$	1.09	0.05
M_{25}: $var(\Delta_2 a_{it})$	1.13	0.07
M_{26}: $var(\Delta_3 a_{it})$	1.18	0.07
M_{27}: $var(\Delta_4 a_{it})$	1.30	0.09
M_{28}: $var(\Delta_5 a_{it})$	1.29	0.08
Measure of labor		

Note: Standard errors were obtained by means of a cluster bootstrapping procedure.

Appendix Table A4.
Additional Estimation Results: With Proxy Variables for Human Capital

Measure of labor	Wage cost (see Table 7)			
	Est.	s.e.		
M1: $corr(\Delta i, \Delta a)$	-0.11	0.01		
M2: $corr(\Delta i, \Delta a_{-1})$	0.06	0.02		
M3: $corr(\Delta i, \Delta i_{-1})$	-0.53	0.01		
M4: $corr(arpk, a)$	0.70	0.01		
M5: $var(\Delta i)$	0.38	0.01		
M6: $var(arpk)$	2.21	0.04		
M7: $corr(i, i_{-1})$	-0.11	0.02		
M8: $var(i)$	0.17	0.00		
M9: $corr(\Delta h, \Delta a)$	-0.07	0.02		
M10: $corr(\Delta h, \Delta a_{-1})$	0.05	0.02		
M11: $corr(\Delta h, \Delta h_{-1})$	-0.55	0.01		
M12: $corr(arpl, a)$	0.90	0.00		
M13: $var(\Delta h)$	0.37	0.01		
M14: $var(arpl)$	1.15	0.02		
M15: $corr(h, h_{-1})$	-0.18	0.01		
M16: $var(h)$	0.16	0.00		
M17: $\hat{r}_{Levels}$	0.44	0.01		
M18: $\hat{r}_{\Delta_1}$	-0.47	0.01		
M19: $\hat{r}_{\Delta_2}$	0.06	0.01		
M20: $\hat{r}_{\Delta_3}$	0.11	0.02		
M21: $\hat{r}_{\Delta_4}$	0.16	0.03		
M22: $\hat{r}_{\Delta_5}$	0.19	0.03		
M23: $var(a_{it})$	0.94	0.02		
M24: $var(\Delta_1 a_{it})$	1.05	0.04		
M25: $var(\Delta_2 a_{it})$	1.12	0.03		
M26: $var(\Delta_3 a_{it})$	1.19	0.03		
M27: $var(\Delta_4 a_{it})$	1.25	0.03		
M28: $var(\Delta_5 a_{it})$	1.30	0.04		
Decision rule $k_{i,t+1}$				
ψ_1 (k_{it})	0.32	0.15		
ψ_2 $(E_t(\tilde{a}_{i,t+1}))$	-0.77	0.33		
ψ_3 (l_{it})	0.10	0.05		
ψ_6 (θ_i)	1.82	0.55		
ψ_7 $(\varepsilon_{i,t+1})$	1.06	0.57		
ψ_8 (χ_i)	1.65	0.41		
ψ_9 $(\bar{a}_i)$				

The table continues on the next page.

Appendix Table A4 (cont'd)

Measure of labor	Wage cost	
	Ethiopia	
	Est.	s.e.
Decision rule l_{it}		
ϕ_1 ($l_{i,t-1}$)	0.17	0.08
ϕ_2 ($\tilde{a}_{it}$)	-0.22	0.08
ϕ_3 (k_{it})	0.47	0.07
ϕ_4 ($E_t(\tilde{a}_{i,t+1})$	-0.11	0.04
ϕ_5 (u_{it})	1.59	0.29
ϕ_6 (θ_i)	2.05	0.12
ϕ_7 ($\varepsilon_{i,t+1}$)	0.08	0.03
ϕ_8 (χ_i)	0.15	0.06
ϕ_9 ($\bar{a}_i$)		

Note: Standard errors are based on a cluster bootstrap procedure.