Firm capacity utilization and cross-country TFP gap*

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Abstract

We argue that firms' capacity underutilization (underemployment of quasi-fixed inputs) could explain significant fraction of cross-country productivity differences. We document that firms in developing countries have significantly lower capacity utilization rate (CUR) than those in emerging and developed countries. We theoretically explore why firms could end up underutilizing their capital and provide strong empirical support for the theoretical predictions. In particular, we find that supply-side constraints such as shortage of material inputs, electricity, water and access to credit explain significant fraction of variation in CUR across firms and countries. Next, we show that measures of TFP that do not account for CUR considerably underestimate 'true' productivity when CUR is low, but not when CUR is high. As a result, about 40% of measured TFP gap between high- and low-income countries could be attributed to differences in the average CUR.

Keywords: Capacity, Capacity utilization, Production Function, TFP, TFP gap. JEL Codes: D21, D24, E22, F14, L25, L60, O47

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1 Introduction

There is a broad consensus that aggregate TFP differences account for more than half of cross-country income gap while physical and human capital differences account for the remaining (Hsieh and Klenow, 2010).[1] The literature provides two potential explanations for the aggregate TFP gap: (i) technology gap that determines the efficiency at which individual firms convert inputs into output (Parente and Prescott, 1994; Frantzen, 2004; Benhabib and Spiegel, 2005), and (ii) policies and institutions that cause misallocation of factors across firms (Restuccia and Rogerson, 2008; Alfaro et al., 2009; Hsieh and Klenow, 2009; Bartelsman et al., 2013). A less explored possibility is that firms across countries could differ in the extent to which they utilize productive factors that exist at their disposal, for various reasons. How much of the TFP gap could be explained by productive factors, such as capital, that are less frequently used (or underemployed)?

In this paper, we argue that capacity underutilization , i.e., underemployment of quasi-fixed inputs by firms, could explain significant fraction of measured TFP gap across countries. Our argument is based on two crucial observations from firm-level data. First, firms in richer countries have significantly higher CUR, on average, than their counterparts in poorer countries. For instance, the average CUR for firms in Niger is 45% while it is 87% for firms in Taiwan. Second, when average CUR is low, measured TFP that does not account for CUR significantly underestimates 'true' productivity (technical efficiency). This is true both over time within a country and cross-sectionally across countries. In other words, computing TFP as the residual using the book value of the capital stock (as opposed the value of capital used in the production process) significantly lowers the residual in the growth accounting exercise or measured TFP. These two facts together imply that significant part of higher aggregate TFP in rich countries, compared to poor countries, is attributed to their higher average CUR. When we estimate TFP accounting for CUR, manufacturing firms in high-income countries are 2.75 times more productive than their counterparts in low-income countries. However, estimated TFP that does not account for CUR implies that firms in high-income countries are 3.90 times more productive than those in low-income countries. That is, not accounting for CUR exaggerates manufacturing TFP gap between high- and low-income countries by about 40%.

We start by theoretically exploring why firms could end up underemploying their capital in general, and more so in developing countries in particular. Our theoretical framework formalizes how supply and demand constraints explain variation of CUR

[1] See also 2005 who discusses development accounting in a great detail. The paper shows that the contribution of TFP gap to cross-country income gap is robust to accounting for quality differences in human capital. However, divergence from Hicks-neutral Cobb-Douglas specification casts doubt on the contribution of TFP gap in development accounting.

across firms in an imperfect competition and heterogeneous firm environment. We use World Bank Enterprise Survey (WBES) which covers firm-level data from over 80 countries to explore the empirical relevance of the theoretical predictions. We show that supply-side constraints such as shortage of material inputs, lack of access to credit, frequent power outage, and shortage of water are the main determinants of firm CUR, and these factors explain significant fraction of lower CUR among firms in poor countries compared to those in rich countries. We find that supply chain problems are perhaps the fundamental causes of lower firm CUR; in particular, firms in economies with underdeveloped manufacturing sector that are reliant on imported intermediate inputs have significantly lower CUR. We also find some evidence suggesting the importance of demand constraint (particularly limited access to national and international markets).

Next, we explore the implications of firm capacity underutilization on the estimation of production function parameters, firm TFP and cross-country manufacturing TFP gap. Estimation of production function parameters and TFP implicitly assumes that inputs under the disposal of firms are fully employed; i.e,[2] firms are producing at their full capacity. However, when firms face binding constraints for flexible inputs (such as material or electricity), they end up underutilizing their quasi-fixed inputs (such as capital). In a typical firm survey, an econometrician observes the firm's book value of capital, and not the exact level of capital utilized. How does underutilization of quasi-fixed inputs and its significant variation across firms within and across countries affect the estimation of firm level TFP, and the comparison of TFP across countries? When firms are constrained in some input markets, the popular production function estimation technique called the control function approach (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015) is no longer valid because one of the main assumptions underlying this approach (the scalar unobservability assumption) no longer holds. Also, it is difficult to infer firm productivity from the relationship between firm input choices and output because more productive firms cannot choose strictly higher inputs if it is constrained (Shenoy, 2021).

We use unique firm-level panel data from Ethiopia to overcome these challenges. The data from Ethiopia includes not only actual material input and output, but also material demand and output if the firms were unconstrained (i.e., material demand and output under full capacity utilization). Combining these data with data on labor and quasi-fixed input of capital,[3] we estimate production function under full

[2]A notable exception here is studies that estimate production function in agricultural setting, where usually distinction is made between, for instance, the area of cultivated land vs. the amount of land held by the farmer. See for instance Ayerst et al. (2020).

[3]We treat capital as quasi-fixed inputs following the literature (see, for instance, Abel (1981)). This is consistent with adjustment cost of capital which are particularly likely to be significant in developing countries such as Ethiopia. Capital goods, such as machineries, are predominantly imported and their installation and initial operation is often undertaken by foreign experts.

capacity utilization and under observed capacity utilization. We show that capacity underutilization leads to downward bias in the coefficients of quasi-fixed inputs (capital) and upward bias in the coefficient of flexible input (labor). Consequently, firm level TFP measures and aggregate TFP estimates that do not account for underutilization of quasi-fixed inputs are misleading and significantly underestimate the 'true' productivity. For instance, aggregate TFP that does not account for CUR could be trending upward, misleadingly suggesting productivity growth, while in reality it is driven by improvements in average firm CUR. Our results based on Ethiopian firms show: (i) cross-sectionally, for firms in the lowest quartile of CUR estimated TFP that does not account for CUR underestimates the true TFP by 77% while for the firms in the top quartile of CUR the magnitude of underestimation is just 6%; (ii) over time, aggregate TFP that is estimated without accounting for CUR underestimates the 'true' aggregate TFP by up to 50% during periods of lower average CUR (about 65%) but such underestimation drops to about 20% when average CUR is about 80% or higher.

Similar analysis using WBES data for about 80 countries shows that, for firms in the lowest quartile of CUR, estimated TFPs that do not account for CUR are lower by 34% compared to TFP that accounts for CUR. However, the extent of this underestimation is only 2% for firms in the top quartile of CUR. The implication is that measured TFPs that do not account for CUR significantly underestimate aggregate TFP in countries with low average CUR, but not in countries with high average CUR. Hence, significant fraction of the cross-country gap in measured TFP is attributed to differences in average CUR across countries, instead of 'true' differences in technical efficiency.

This paper is closely related to studies that explore implications of measurement error in capital on estimation of production function and TFP (Galuscak and Lizal, 2011; il Kim et al., 2016; De Loecker et al., 2016). These papers focus on methods of estimating production function consistently in the presence of measurement error in capital. This measurement error could be classical measurement error in the level of capital stock of a firm or measurement error in the capital services due to lack of information on the utilization rate of the capital stock. Given data on direct measure of firm capacity utilization rate, the current paper explores the implications of this second source of measurement error in capital on the estimation of TFP and its cross-country comparison.

A vast literature in macroeconomics studies how variable capacity utilization propagates technology shock or demand shocks and generates endogenous persistence in business cycle models (Greenwood et al., 1988; Fagnart et al., 1999; Savagar and Dixon, 2020; Sun, 2020). More recently, Boehm and Pandalai-Nayar (2022) show how firm-level capacity constraints could generate a convex industry supply while (Comin et al., 2020; Huo et al., 2020) show that accounting for CUR in the estimation of industry TFP has a major impact on the volatility and cyclicality of industry and aggregate TFP. Our paper is closely related to (Comin et al., 2020; Huo et al., 2020), in that we evaluate the effect of capacity underutilization on the estimation of TFP. However, our approach significantly differs from theirs in that we are more focused on how capacity underutilization affects the estimation of production function and firm-level TFP while their paper focuses on how accounting for CUR in the Solow residual affects the estimated industry TFP using industry-level data from major European countries and the U.S. A separate micro literature studies how firms end up underutilizing their capacity due to constraints in input markets (Sahay, 1990).[4] We introduce firm heterogeneity explicitly to these models and evaluate their empirical relevance.

Another literature studies the empirical estimation of production function parameters and firm TFP (Blundell and Bond, 1998; Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015; De Loecker, 2011; De Loecker et al., 2016). These studies implicitly assumed that firms fully utilized both their quasi-fixed and flexible inputs each period. More recently, Shenoy (2021) studies how the estimation of production function is affected when some firms are constrained in the input market. We contribute to this literature by documenting the biases in production function parameters and firm TFP by exploiting a unique firm-level panel data from Ethiopia that includes actual and full capacity production information, which allows us to estimate the production function parameter under observed capacity utilization and full capacity utilization.

This paper is also related to the literature on firm productivity and within-industry resource misallocation (Syverson, 2011; Hsieh and Klenow, 2009; Restuccia and Rogerson, 2017; Bartelsman et al., 2013; Gilchrist et al., 2013; Midrigan and Xu, 2014). Most of these papers particularly focus on the effect of capital misallocation between firms (as measured by between-firm dispersion in marginal revenue product of capital) on aggregate and industry productivity. We complement this literature by showing that variation in marginal revenue product of capital across firms is also consistent with the situation where firms face different level of constraints in the flexible inputs (such as material or electricity) which generates variation in the 'frequency' to which their quasi-fixed is employed, and the marginal revenue products of quasi-fixed inputs between firms. That is, in effect, variation in CUR across firms have similar (to capital misallocation between firms) effect on aggregate productivity by introducing between firm variation in the marginal revenue product of capital.

[4] An older literature explores how investment in excess capacity to deter entry (Spence, 1977; Dixit, 1980; Bulow et al., 1985) and economies of scale in investment (Manne, 1961, 1967; Srinivasan, 1967) could lead to capacity underutilization.

Lastly, we contribute to a relatively underdeveloped empirical literature on the firm capacity utilization (Lieberman, 1987; Tian, 2016; Zhang, 2022). Compared to these papers, our rich data from several countries across the world allows us to look into various potential factors that drive firm capacity utilization. We also extend this literature to explore the potential consequences of lower CUR on estimation of aggregate TFP and resource misallocation.

The rest of the paper is organized as follows. Section 2 describes the data and provides important definitions and cross-country descriptive results. Section 3 presents the theoretical framework and Section 4 provides empirical results supporting the theoretical predictions. Section 5 presents results for the implications of variation in firm CUR on the estimation of production function, TFP and misallocation. Section 6 concludes the paper.

2 Data

2.1 Data sources

The main dataset used in this study is the World Bank Enterprise Survey (WBES), which covers sample of firms from over 100 countries since 2006. The unique feature of this dataset that makes is appealing for this study is that survey instruments are standardized across countries and the data collection is centrally administered by the WB. This is crucial in that firm performance measures can be compared across countries because standardized methodologies and variable definitions are made across the countries. This has been a notorious challenge for studies that combine independent survey from different countries that often have different sampling methodologies and different definitions of variables. The WBES includes not only standard firm characteristics and performance measures but also include a measure of firm capacity utilization rate.

We supplement the WBES dataset with a unique manufacturing survey from Ethiopia called Large and Medium Scale Manufacturing Survey (LMSMS).It is a long panel covering 1996-2017. The unique feature of this dataset is that it includes firm production information both under actual capacity utilization and under full capacity utilization. This allows us to explore how constraints faced by firms in the input and product markets could lead to biases in the estimation of production function and TFP, by comparing production function parameters and TFP estimated from the observed data and from input and output measures under full capacity production. We also exploit the long panel nature of the dataset to explore how informative firm CUR is about the firm's overall performance, such as firm deaths, in comparison to standard measures of firm performance such as firm TFP. We also use UNIDO-INDUSTAT and UN commodity trade datasets to construct import penetration measure at two-digit industrial classification (ISIC-3).

2.2 Capacity utilization: definition and relevance

Capacity utilization is the ratio of actual level of output in a specified period of time to a sustainable maximum level of output (capacity) that a firm can produce under a realistic working schedule, taking into account normal downtime (Corrado and Mattey, 1997). Capacity output can be considered as engineering estimate of the plant's production capacity under realistic working schedule, allowing for regular maintenance times.

Why do we care about CUR of firms? Or how informative is firm CUR about overall firm performance, e.g., in predicting firm exit or growth? In the macroeconomics literature, CUR is considered as important indicator of inflationary pressures and business cycle fluctuations and as a mechanism through which technology shock propagates and generates endogenous persistence (see, for instance, Corrado and Mattey 1997; Fagnart et al. 1999; Boehm and Pandalai-Nayar 2022; Zhang 2022).

From microeconomic perspective, CUR is important for at least two reasons. First, as we show in our main analysis, measured TFP that does not account for CUR underestimate the true level of productivity when CUR is low. Second, we argue that CUR is very informative about the firm's performance. As a simple example, we ask to what extent CUR predicts firm death with and without conditioning on firm TFP. Table A.3 presents the results based on our Ethiopian panel data. To facilitate the comparison between CUR and TFP, we have standardized both measures. In the first three columns, we include industry (4-digit ISIC) fixed effects whereas in the last three columns we include firm fixed effects. The results across all the specifications show that firm CUR is an important predictor of firm exit/survival, even conditioning on firm size, TFP and firm fixed effect. In our preferred specifications with industry fixed effects, the coefficient of CUR is the same magnitude as that of TFP.

2.3 Cross-country variation in firm CUR

Next, we explore variations in firm CUR across countries. Figure 1 plots average CUR against log GDP per capita. The figure shows two important results. First, there is substantial variation in the average CUR across countries: the average CUR ranges from 45% for firms in Niger to 87% for firms in Thailand. Second, average CUR is strongly positively correlated with log GDP per capita (a correlation of 0.45). Firms in poorer countries have significantly lower CUR, on average, compared to their counterparts in richer countries.

We farther explore factors that explain cross-country variation in average CUR and its positive correlation with GDP per capita in figures 2-7. Figure 2 plots aggregate CUR against manufacturing value-added as a percentage of GDP (which we use as a proxy measure of the level of domestic manufacturing development). The figure shows a strong positive correlation of 0.54 between aggregate CUR and the size of manufacturing sector. Inspection of the scatter plots shows that aggregate CUR is significantly larger in countries with vibrant manufacturing sector such as China, Thailand, and Indonesia, and it is significantly lower in countries where manufacturing sector is poorly developed such as Malawi, Zimbabwe, and Niger. While we are not suggesting that this result has a causal interpretation (perhaps one may argue reverse direction of causation), we believe that this correlation, in combination with other similar correlations presented below, is indicative of the potentially important role of supply chain factors (particularly, the availability of intermediate inputs in domestic markets) in firm CUR.

Figures 3-5 present the effects of supply side constraints. Figure 3 plots aggregate CUR against the fraction of firms reporting having an active credit line (proxy for access to credit). The figure shows a positive correlation of 0.3 between average CUR and access to credit. In Zimbabwe, only 10% of the firms reported to have access to credit and the average CUR is less than 50% whereas in Thailand more than three-quarters of the firms have access to credit and the average CUR is over 87%. Figure 4 shows the relationship between the fraction of firms in a country reporting shortage of water for their manufacturing activity and the average CUR. The figure shows a strong negative correlation of -0.44 between water shortage and average CUR. For instance, in countries such as Thailand, Indonesia, Czech Republic, Slovenia and China, very tiny fraction of firms report to have experienced water shortage and the average CUR in these countries is over 80%; in Niger and Zimbabwe more than one-fourth of the firms report water shortage had disrupted their production and average CUR is below 50%. Figure 5 presents similar result for electricity shortage (the fraction of firms which report to have several disruptive power blackout during the year). The vast majority of these firms report multiple power blackout in a month. The figure shows a negative correlation between power blackout rate and average CUR. The correlation is weaker than the one between water shortage and average CUR. This is perhaps due to the fact that power blackout is also pervasive in relatively advanced countries. E.g., nearly half of firms in China report to have experienced disruptive power blackout. However, in such countries, firms overcome the challenge of power blackout by using generators.

Figures 6 and 7 present the effects of input sources and export participation. Figures 6 shows that in countries where imported intermediate inputs are the main source of material input, aggregate CUR is lower. This is perhaps because, when firms are using domestic inputs, they do not have to deal with lengthy bureaucratic processes to obtain import licences and customs clearance, and in some countries, there are significant hurdle to secure foreign exchange required for imports. Firms in major manufacturing countries such as China, Thailand, India and Indonesia are less reliant on imported intermediate inputs and have much higher CUR than firms in, e.g., Niger. This suggests that domestic supply chain is probably crucial factor in driving aggregate CUR. Figure 7 presents the effect of access to foreign product market. Aggregate CUR is higher in countries where firms are more export oriented, but the correlation is weak.

Overall, the above results strongly suggest that supply constraints are the main reasons behind lower average CUR in poorer countries compared to richer countries.

Table A.4 gives detailed country-level summary statistics for average CUR and other important characteristics for a subsample of countries that are used in our main analysis. The table shows significant heterogeneity in CUR and the extent to which firms are constrained in the input markets such as intermediate inputs, electricity, water, and access to credit across countries within continent. Below, we explore how these constraints influence firm CUR.

3 Theoretical model

The model below formalizes the role of supply and demand constraints in explaining variation in firm CUR. First, firms often face binding constraints in the input markets such as imported and local materials, electricity, water, etc. For a given capacity, such shortage of variable inputs may force firms operate below their full capacity. Similarly, firms may face lower demand (at their minimum profitable price) than they could serve with their production facilities which results in firms operating with excess capacity.

3.1 The model

We assume firms are heterogeneous in their productivity where each firm i draws its productivity $A_i > 0$ from a probability distribution function $F(A)$. The technology of firms is given by the following Leontief production function:[5]

$$y_i = A_i \min\Big[\min\Big[\frac{x_{i1}}{\alpha_1}, ..., \frac{x_{in}}{\alpha_n}\Big], k_i\Big] \tag{1}$$

[5]Leontief technology is chosen because it is convenient to think about the concept of capacity and its utilization rate. This is inline with previous studies that model capacity utilization (see, for instance, Fagnart et al. 1999, Greenwood et al. 1988, and Sahay 1990). Below, when we endogenize the firm's choice of capital/capacity, we assume that firms use a putty-clay technology: capital and labor are substitute ex ante (i.e., before investing) but complement ex post (i.e., once equipments are installed). This means that each firm makes a capacity choice when investing (Fagnart et al., 1999).

where $x_{ij}, \quad j = 1, ..., n$ are variable inputs such as material, electricity, water, labor, etc., k is capital stock, and $\alpha_1, ..., \alpha_n$ are parameters. Suppose $\frac{x_{im}}{\alpha_m} = \min[\frac{x_{i1}}{\alpha_1}, ..., \frac{x_{in}}{\alpha_n}]$ is the most binding variable input constraint. Then, equation 1 can be rewritten as

$$y_i = A_i \min\Big[\frac{x_{im}}{\alpha_m}, k_i\Big] \tag{2}$$

We assume that the firm operates in an imperfectly competitive industry and faces a downward sloping demand function $P(y)$ which satisfies $P\ (y) \le 0$ and $P\ \ (y) \ge 0$. Let p_x is the price of variable input x_m. From now on, we drop the firm index for brevity of notations.

Fixed capital: Consider a case where the firm has a fixed capital and maximizes profit by choosing optimal amount of x_m, given the technology, productivity, demand and the price of the variable input. This can be thought of as a short run problem where the firm cannot adjust its physical capital such as machineries. The optimal condition is given by $y = A\frac{x_m}{\alpha_m} = Ak$. Profit is given by:

$$\Pi = yP(y) - \frac{\alpha_m}{A} p_x y \tag{3}$$

The profit maximizing level of production is given by y_f and satisfies the following condition $P(y_f) + y_f P\ (y_f) = \frac{\alpha_m}{A} p_x$. We refer to y_f as unconstrained profit maximizing level of production.

Now suppose that the firm faces a constraint in the variable input market. Examples include: frequent power outage, shortage of water, limited access to imported intermediate inputs (e.g., due to foreign exchange or import license rationing by a government or unexpected delays on customs clearing), etc. Let the firm's input constraint is $x_m \le \bar{x}$. The optimal conditions for maximization of profit in equation 3 subject the input constraint are:

$$P(y) + yP\ (y) = \frac{\alpha_m}{A}(p_x + \lambda)$$
$$\lambda[x - \bar{x}] = 0$$

where λ is the Lagrange multiplier. If the input constraint is not binding ($\lambda = 0$), the optimal output is given by y_f. If the input constraint is binding, $\lambda = 0$, the optimal output $y\ $ satisfies $P(y\ ) + y\ P\ (y\ ) = \frac{\alpha_m}{A}(p_x + \lambda)$. Given the demand property, it can be shown that $y\ < y_f$.[6] The resulting capacity utilization rate of the firm is

[6]To see this, note that $\frac{\alpha_m}{A}(p_x + \lambda) > \frac{\alpha_m}{A} p_x$ implies that $P(y\ ) + y\ P\ (y\ ) > P(y_f) + y_f P\ (y_f)$. Rewrite this as $P(y\ ) - P(y_f) + y\ P\ (y\ ) - y_f P\ (y_f) > 0$. Adding and subtracting $y\ P\ (y_f)$, we can rewrite the above as $P(y\ ) - P(y_f) + y\ (P\ (y\ ) - P\ (y_f)) + (y\ - y_f)P\ (y_f) > 0$. If $y\ < y_f$, all the terms on the left-hand side are positive given the demand properties of $P\ (y) < 0$ and

given by $\frac{y^*}{y_f^*} < 1$. Note that, the more stringent the input constraint is, the larger λ would be and the lower the firm CUR. Qualitative evidence from WBES shows that firms from less developed countries are not only more likely to face binding input constraints (e.g they are more likely to have faced a power outage that disrupts their production during a fiscal year) but also that the constraints they face are likely to be stringent (e.g., they face several days of power outage per month).

Another mostly cited reason for lower CUR in the qualitative data is demand constraint. Suppose y^d is the quantity demanded at the lowest possible price $\underline{p}$ at which the firm can make positive profit, $y^d \equiv y(\underline{p})$. The firm's profit maximization subject to this constraint has the following Kuhn-Tucker conditions:

$$P(y) + yP\,(y) = \alpha_m(p_x + \lambda^d)$$
$$\lambda^d[y - \bar{y}^d] = 0$$

where λ^d is the Lagrange multiplier associated with the demand constraint. If the demand constraint is not binding, $\lambda^d = 0$ and $y\ \ = y_f < y^d$ (assuming that there is no binding input constraint). However, if the demand constraint is binding ($\lambda^d = 0$), then $y\ \ = y^d < y_f$. That is, the profit maximizing output is determined by the demand constraint and the firm ends up producing below its full capacity. The resulting CUR is given by $\frac{y^d}{y_f^*} < 1$.

4 Empirical investigation

The theoretical framework presented above implies some testable implications. The first is that demand constraints, such as lack of access to national/international markets, may limit firms from utilizing their full production capacity. The second is that supply-side constraints such as lack of access to credit, frequent power outage, shortage of water, etc could explain capacity underutilization. We use WBES data to assess these testable implications. We first briefly discuss how we measure firm-level demand and supply constraints below.

4.1 Measurements

The theoretical model above suggests that demand and supply constraints may explain heterogeneity in firm CUR. To test the validity of these predictions empirically, we need to identify measures of these factors.

$P\ \ (y) > 0$. As a simple example, consider the following constant elasticity demand $y = p^{-\varepsilon}$. The optimal production with and without the input constraint are given by $y_f\ = [\frac{\varepsilon}{\varepsilon-1}\frac{\alpha_m}{A}p_x]^{-\varepsilon}$ and $y\ \ = [\frac{\varepsilon}{\varepsilon-1}\frac{\alpha_m}{A}(p_x + \lambda)]^{-\varepsilon}$, respectively. The resulting CUR is $\frac{y^*}{y_f^*} = (\frac{p_x}{p_x+\lambda})^{\varepsilon} < 1$. Note how CUR is strictly decreasing with .

We measure the demand side factors using the following list of questions in the survey (paraphrased for brevity):

(i) *Which of the following was the main market in which this establishment sold its main product?* The list of alternatives are: 1 for local market, 2 for national market and 3 for international market. This variable measures a firm's market access in the sense that firms that have access to national and international market are less likely to be demand constrained compared to those that compete only in local markets.

(ii) *What percentage of this establishment's sales were exported (directly or indirectly)?* This measure captures the export intensity of the firm. This variable is strongly correlated with the international market category in (i).

(iii) *Does this establishment compete against unregistered or informal establishments?* This captures whether competition with informal sector (such as contraband goods) affects the firm's demand and CUR.

(iv) *How many competitors did this establishment's main product face in this main market?*

(v) Import penetration rate: we construct industry-level measure of import penetration rate using trade data and industry-level manufacturing data as log of $\frac{\text{industry import}}{\text{industry output}} \times 100$. This measures competition with foreign firms in the domestic market.

We measure the supply side factors using the following list of variables:

(i) *What percentage of this establishment's purchases of material inputs or supplies were from import?* This measure captures import constraints (such as foreign exchange or import license rationing) for firms that rely on imported inputs.

(ii) *During the fiscal year, did this establishment experience power outages that a ected production?* This is a dummy variable which equals 1 if the firm faced power outage and 0 otherwise.

(iii) *During the fiscal year, did this establishment experience insu cient water supply for production?* This is a dummy variable which equals 1 if the firm faced water shortage and 0 if not.

(iv) *Does this establishment have a line of credit or a loan from a financial institution?* This is a dummy variable which equals 1 if the firm has access to loan and 0 if not.

In addition to the above variables, we also include variables that our theory does not capture but are likely to cause omitted variable bias if excluded. These variables are: dummy variables for three firm size categories (small (<20 workers), medium (20-99 workers), and large (100 or above workers)), dummy variables for firm age groups (age 0-5, age 6-10, age 11-20, age 21-50, and age 51 or above), and fraction of ownership by foreigners and by government. We also include log GDP per capita and industry (ISIC 2-digit), year and country fixed effects.

We run the following regression to explore firm and industry level factors affecting CUR:

$$\text{CUR}_{ijct} = \alpha_0 + \alpha \mathbf{X}^d_{ijct} + \beta \mathbf{X}^s_{ijct} + \gamma \mathbf{Y}_{ijct} + \eta_j + \eta_c + \eta_t + \varepsilon_{ijct} \tag{4}$$

where i, j, c, and t index firm, ISIC-2digit industry, country and year, respectively, CUR is firm capacity utilization rate measured in percent, $\mathbf{X}^d$ is a vector of variables measuring demand constraint, $\mathbf{X}^s$ is a vector of variables measuring supply constraint, N is log number of direct competitors a firm faces, Y is a vector of control variables including firm size, age, and ownership, and η_j, η_c and η_t are industry, country and year fixed effects, respectively. We cluster standard errors two-way across industries and countries. We estimate this equation using both OLS and Tobit (to account for censoring of CUR from above at 100). We suggest caution in interpreting the estimated results as causal effects. While most of the regressors listed above are exogenous to the firm, the estimated coefficients could be biased by omitted variables that are correlated with the regressors. To minimize such concerns, we include a host of control variables and fixed effects.

4.2 Results

Table 1 reports the results of estimating equation 4. We report the OLS and Tobit estimation results in columns 1 and 2. The Tobit estimation captures the censoring of the dependent variable at 100 percent. Close to 20% of the observations are censored at 100 percent, which represents the fraction of firms reporting full CUR in the data. These firms are predominantly from high-income countries.

Panel A reports variables capturing demand constraint. The first measure of demand constraint is a factor variable that takes three values (1 if main market of the firm is local market, 2 if main market is national market or 3 if the main market is international market). The first category is dropped (a base category). The coefficients of the national market are positive and statistically significant in the Tobit specification. The coefficients imply that firms that compete at national and international level have 2 percentage point higher CUR than those that compete only at the local market. The second demand constraint measure is the fraction of export in firm sales. This variable is strongly correlated with the third category of the above variable and is statistically insignificant.[7] Dropping this variable increases the coefficient and precision of the international market dummy. The next two measures of demand constraint measure the role of competitions from imports and informal sectors. The coefficients of log import penetration rate and Competition with informal firms are both negative but statistically insignificant. Potential explanations for the insignificance on import penetration is that IP includes both imported final goods and imported intermediate goods. For example, Ngoma (2022) finds that 78.5% of Ethiopia's imports from China are intermediate inputs. A potential explanation for the insignificant result on competition with informal firms is that formal and informal firms tend to operate in different markets and this is especially true for the large formal firms.

Panel B reports the result for variables that capture supply side constraint. The first variable is the share of material input imported and it has a negative and statistically significant effect on firm CUR, implying that firms which rely more on imported intermediate inputs have significantly lower CUR (this also holds at aggregate level, see figure 6). Note that this is cross-sectional variation at a point in time as opposed to studying the impact of imported intermediates over time within a firm where it is possible find that increases in imported intermediate inputs increase the CUR. In the data, the share of imports in intermediate input range from 0 to 100 percent, with an average of 25 percent. Together with the point estimate, this suggests that firms that rely 100% on imported inputs have lower CUR by about 1.5 percentage points compared to those that do not use imported inputs. Older literature attributed this to trade barriers that make accessibility of imported inputs difficult for domestic firms (Sahay, 1990). However, the qualitative questions in WBES suggest that longer period of customs clearance, and rationing of import license and foreign exchange are potential explanations. Power outage is one of the most important supply-side constraint faced by firms, particularly in developing countries. Firms that experienced disruptive power outage during the year have lower CUR by about 2 percentage points than those that did not. Another equally important supply-side constraint is water shortage, which has similar magnitude of effect on firm CUR. The third variable capturing supply side constraint is access to credit (if a firm has credit line). Not surprisingly, firms with access to credit have significantly higher capacity utilization rate. Firms that have at least one active credit line have more than 2% higher capacity utilization rate, on average, than those which do not.

Turning to the control variables, the size and precision of the coefficient of log GDP per capita suggests that firms in advanced countries have significantly higher

[7] Tian (2016) finds that exporters have higher capacity utilization rate compared to non-exporters using data from China.

CUR, on average, compared to firms in less developed countries. One log-point increase in GDP per capita is associated with approximately 18 percentage point higher average CUR (in the data, log GDP per capita ranges from 5.8 to 10.5, with an average value of 8.2). Foreign ownership tends to have insignificant effect on CUR, though government ownership tends to decrease CUR. A firm that is 100% government owned has lower CUR by 4 percentage point compared to a firm with zero percent government ownership. Older firms (above 20 years) tend to have significantly lower capacity utilization rate compared to the baseline group of firms aged 0-5 years old. The coefficient for log number of direct competitors of the firm, which suggests that competition may improve capacity utilization. Finally, the coefficients of the size dummies indicate that CUR increases with firm size measured in number of workers. Compared to the baseline group of small firms (<20 workers), medium-sized firms (20-99 workers) have higher CUR by 2.8 percentage points and large firms (100 or above workers) have higher CUR by about 6.6 percentage points.

To sum up, the above analysis shows that underutilization of capacity by firms is strongly associated with the supply-side constraints they face in their environment. The results in section 2 show that firms in poorer countries are more likely to face such constraints, compared to their counterparts in developed countries. In the next section, we investigate the implications of this systematic variation in capacity underutilization for estimation of TFP and its cross-country comparison.

5 CUR and bias in measured TFP

In this section we demonstrate how capacity underutilization biases production function parameters and measured TFP. To do so, we first exploit our rich and long panel data from Ethiopia, which enables us to consistently estimate the production function parameters (with accounting for CUR) and the bias in measured TFP that results from not accounting for CUR. We explore how this bias varies across cross-section of firms with different level of CUR and the time series relationship between biases in measured TFP and average CUR. Next, we use our WBES data to explore whether similar conclusion can be drawn by comparing cross-section of countries. The caveat in this second exercise is that because WBES is essentially cross-sectional at firm level, we cannot consistently estimate production function using state of the art methodologies that address endogeneity of input choices.

Suppose the production function takes the following standard Hicks-neutral form.

$$Y_{it} = e^{\omega_{it}+\varepsilon_{it}} F\Big(K_{it}, L_{it}, M_{it}\Big) \tag{5}$$

where i indexes firms and t indexes year, Y is output/revenue , K is physical capital which includes the book value of machineries and buildings, L is labor input (production and administrative workers), and M is material input which includes raw materials and intermediate inputs. Productivity consists of a persistent component ω_{it} and a productivity shock ε_{it} (which can also be interpreted as random measurement error in output). We make the following assumptions regrading the timing of the firm's decisions.

Assumption 1. *K is quasi-fixed input, i.e. predetermined.*

We assume that the available level of capital at the beginning of period t is predetermined in period $t-1$. In particular, we assume that the firm cannot adjust their choices of K_t after observing the constraints they face in the flexible inputs in period t.

Assumption 2. *L and M are fully flexible inputs.*

We assume that firms choose their labor and material inputs in each period and the firms' intermediate and labor demands depend on their productivity in period t, ω_t as well as demand and other market conditions in that period. While treating material/intermediate inputs as flexible input is not controversial, the case of labor is more subtle and depends on institutional constraints such as hiring and firing costs. At least in the case of Ethiopia, the hiring and firing costs are non-negligible for permanent employees. However, if one considers labor input as number of workers $\times$ hours per worker, firms may adjust their labor demand via the intensive margin (hours per worker) more easily even if the regulatory environment makes adjustment on the extensive margin (number of workers) relatively more difficult. Unfortunately, we do not observe hours of work in our data. We investigate the sensitivity of our results to the treatment of labor as quasi-fixed in Appendix C.

Assumption 3. *The persistent component of productivity follows AR(1) process.*

More specifically, we assume that productivity follows the following process

$$\omega_{it} = \rho\omega_{it-1} + \epsilon_{it} \tag{6}$$

where ω the persistent component of productivity, and ϵ is a random error.

Assumption 4. *Firms face constraints for some of their flexible inputs.*

This assumption is motivated by the analysis in the previous sections where we show that significant fraction of firms face constraints in input markets such as material, electricity, water, loan, etc. While firms in developing countries are more likely to face more stringent constraints in one or more inputs, we have shown that firms in developed countries also face similar constraints albeit less stringent one.

To fix idea, we assume firms face constraints in the material input market. The firm maximizes expected profit net of material and labor costs. The Lagrangean for the firm's optimization problem, conditional on predetermined capital, is given by:

$$\mathsf{L} = E\Big[P_t\Big(e^{\omega_{it}+\varepsilon_{it}}F\Big(K_{it}, L_{it}, M_{it}\Big)\Big)\Big] - wL_{it} - P^m M_{it} - \lambda_{it}\Big[M_{it} - \bar{M}(\mathbf{X})\Big] \quad (7)$$

where E is expectation over the distribution of productivity shock ε, and P_t is product price.

Assumption 5. *λ_{it} is unknown to the firm before period t, i.e., the firm cannot predict the extent of future constraints.*

Assumptions 1-5 imply that if the firm's material constraint is binding, the firm's previous period choice of K is inconsistent with the constrained optimal level of material and labor chosen in period t.

To clarify the implication of constraints on estimation of production function, we now make distinction between two data: (i) $\{Y^f, K^f, L^f, M^f\}$ which denote, respectively, output/revenue, capital input, labor and material when the firm operates at full capacity (without constraints), and (ii) $\{Y, K^f, L, M\}$ which denote, respectively, the observed level of output/revenue, capital, labor and material. When (some) firms face binding constraints in the flexible input market, the level of flexible inputs they employ and the resulting output may differ from the unconstrained values, more specifically $Y \leq Y^f$, $L \leq L^f$, $M \leq M^f$. Note, however, that the observed capital level is the total capital stock of the firm regardless of whether it is fully employed or not during the year of survey.

The data that is reported in most surveys is $\{Y, K^f, L, M\}$. When this data is used in estimation of production function and TFP, the implicit assumption is that the firm's reported level of capital K^f is fully employed during the specific year. However, when (some) firms are constrained in employment of flexible inputs such as material and labor (or other inputs not explicitly included here such as electricity and water), they will not be able to fully employ the available capital. There are two major issues with estimation of production function using the data $\{Y, K^f, L, M\}$. First, the assumption of scalar unobservability (Olley and Pakes 1996; Levinsohn and Petrin 2003; Ackerberg et al. 2015) is no longer satisfied if (some) firms are constrained which makes the widely used estimation technique of the control function approach invalid. This is because, if firms face binding material constraint, the firm's material demand function involves two unobserved variables: the productivity measure ω and the Lagrange multiplier corresponding to material constraint λ. Thus, the usual approach of inverting the material demand equation to write the unobserved productivity term ω as a function of observables and use this function as a control of ω in the production function is impossible because the inverted function includes unoberved term, λ. However, this problem can still be overcome using other production function estimation techniques such as dynamic panel approach, which do not rely on the assumption of scalar unobservability.

Second, and perhaps a more serious problem is that, if the firm's material choice is made under a binding constraint, the choice of M is inconsistent with the level of predetermined input K^f and the corresponding output Y is a constrained optimal level. That is, if material choice is constrained, the predetermined inputs would end up underutilized (underemployed). Thus, one cannot identify the true production function parameters from data on $\{Y, K^f, L, M\}$ if firms face binding material constraint. Moreover, we cannot infer a firm's productivity from its input choices because a more productive firm cannot choose strictly higher inputs if it is constrained (Shenoy, 2021).

Below we discuss how we overcome these challenges and estimate the production function and the bias in TFP estimation using our unique panel data from Ethiopia. To do so, we specify the production function as Cobb-Douglas.

5.1 Ethiopian panel data

Consider the following production function:

$$Y_{it}^f = e^{\omega_{it}+\varepsilon_{it}}(K_{it}^f)^{\beta_k}(L_{it}^f)^{\beta_l}(M_{it}^f)^{\beta_m} \tag{8}$$

where Y^f, K^f, L^f, M^f are, respectively, output/revenue, capital, labor and material if the plant operates with its full production capacity. β_x is output elasticity with respect to input $x \in \{K^f, L^f, M^f\}$. ω is the persistent component of the firm's productivity (TFP) whereas ε is productivity shock or output measurement error. If data on $\{Y^f, K^f, L^f, M^f\}$ is available, one can consistently estimate the output elasticities and TFP.

As stated above, in a typical firm level survey data, an econometrician observes only actual output and input demands, not output and input demands under full capacity. That is, the econometrician observes $\{Y, K^f, L, M\}$ and ends up estimating the following production function:

$$Y_{it} = e^{\tilde{\omega}_{it}+\varepsilon_{it}}(K_{it}^f)^{\alpha_k}(L_{it})^{\alpha_l}(M_{it})^{\alpha_m} \tag{9}$$

The output elasticities and TFP estimated from equation 8 are different from those obtained from equation 9. If one observes the utilized level of capital (which we denote by K), one can consistently estimate the output elasticities and TFP by replacing K^f by K in equation 9, and the estimated output elasticity and TFP should be the same as those obtained from equation 8. In other words, in a situation where most firms operate at below their full production capacity, identification of the output elasticities and TFP requires observing $\{Y^f, K^f, L^f, M^f\}$ in equation 8 or $\{Y, K, L, M\}$ in equation 9 where K is the utilized level of capital input.

In our Ethiopian data we do not observe the utilized level of capital K, so we cannot estimate equation 9 by replacing K^f by its utilized value K. We thus estimate output elaticities and TFP from equation 8. In equation 8, we observe $\{Y^f, K^f, M^f\}$ but not L^f. We infer L^f by combining the firm's profit maximization conditions under full capacity and when they are constrained (observed scenario) which are given as follows:

$$M^f = \frac{\beta_m}{\beta_l}\frac{w}{P_m}L^f \quad \text{under full capacity} \tag{10a}$$

$$M = \frac{\alpha_m}{\alpha_l}\frac{w}{P_m + \lambda_i}L \quad \text{constrained} \tag{10b}$$

where λ_i is the Lagrange multiplier for material constraint. Combining the two equations we obtain $L^f = \gamma\frac{P_m M^f}{(P_m+\lambda_i)M}L$.[8] Note that $P_m M^f$ and $(P_m + \lambda_i)M$ are material expenses under full capacity and under constrained optimization, respectively. That is, we can obtain L^f by scaling up L by the ratio of material expense under full capacity to the constrained (observed) material expense, up to a constant factor. We can thus consistently estimate equation 8 using data on $\{Y^f, K^f, M^f\}$ and our inferred measure of L^f.

To estimate the bias in TFP that results from estimating equation 9 instead of equation 8, we proceed as follows. Taking logs of both equations and subtracting:

$$y_{it} - y_{it}^f = \gamma_0 + (\alpha_k - \beta_k)k_{it}^f + \alpha_l l_{it} - \beta_l l_{it}^f + \alpha_m m_{it} - \beta_m m_{it}^f - \underbrace{(\omega_{it} - \tilde{\omega}_{it})}_{\text{TFP bias}} + \varepsilon_{it} \tag{11}$$

where lower case letters denote log values. Notice that the left-hand side expression is log of capacity utilization rate that we observe directly from the data, $\ln\text{CUR} \equiv y_{it} - y_{it}^f$. This equation makes it clear that the bias in measured TFP $\omega_{it} - \tilde{\omega}_{it}$ decreases when CUR increases. As CUR approaches 100%, the bias in measured TFP converges to zero. Also, TFP estimated from equation 9 ($\tilde{\omega}_{it}$) underestimates the true TFP (ω_{it}), so that the TFP bias $\omega_{it} - \tilde{\omega}_{it}$ is positive for firms that operate at below their full capacity.

Using equation 11 to estimate the TFP bias has some important advantages over estimating equations 8 and 9 separately and comparing their TFP measures. Taking difference between equations 8 and 9 will wash out unobserved factors that might influence input demands under both full capacity and constrained optimization

[8] Where $\gamma = \frac{\beta_l \alpha_m}{\beta_m \alpha_l}$.

scenarios. Also, firm-year specific measurement error that is common across the observed output and output under full capacity will be washed out when we take difference across the two equations. Nevertheless, estimation of equation 11 requires some caution because, theoretically, it suffers from the same endogeneity problems faced when estimating production function. More specifically, the level of inputs chosen by a firm is likely to be influenced by the firm's productivity, both when the firm is producing at full capacity and when the firm is operating at below capacity. To address this concern we estimate equation 11 using dynamic panel, in addition to OLS. Indeed, we show that results are quite similar across OLS and dynamic panel approaches.

To investigate the extent of bias in the production function parameters (output elasticities) due to estimation of equation 9 instead of equation 8, we estimate each of these equations using dynamic panel approach. Note that, parameters estimated from equation 9 are biased because the specification assumes firms' available capital inputs are full employed, while in reality the utilized level of capital is likely to be significantly less than the measured capital for firms that have lower CUR.

Results

We first report and discuss the results for bias in TFP estimated from equation 11. We present both OLS and dynamic panel results but, our discussion here is based on the latter (though the two approaches give very similar results).

Figure 8 plots the estimated TFP bias measured as $\frac{\text{Adjusted TFP}}{\text{Non-adjusted TFP}} = \exp(\omega_{it} - \tilde{\omega}_{it})$ against the firm CUR. Each dot in the figure represents firm-year observation, and the fitted line is fractional polynomial fitting (with 95% CI) to capture the curvature in the scatter plot. The figure reveals two main results. First, it shows that the estimated TFP bias decreases with CUR and tends to converge to 1 as CUR approaches 100%. This is consistent with our theoretical prediction. Note that small fraction of firms in Ethiopia report CUR of above 100%. This happens when firms face significant positive demand shocks and try to meet it by operating over their regular production capacity.[9] For such firms, measured TFP that does not account for CUR overestimates their 'true' TFP, because it does not take into account the fact that the capital input has been used more intensively than it is regularly. Figures A.1 and A.3 present similar results obtained from OLS and industry-level estimation of the dynamic panel (where we allow the α s and β s to vary across

[9]For example, Ethiopia experienced significant construction boom during the sample period, which led to skyrocketing prices of construction materials such as cement. Firms that manufacture products used in construction sector would seize such opportunity to produce beyond their regular production capacity. Another example is frequent shortage of food products such as sugar and oil which allows existing firms to expand production beyond their regular production capacity if unconstrained by inputs.

two-digit industries). The OLS result is very similar to the the main result. The scatter-plots based on industry-level estimation of equation 11 tell similar story as the main result though it shows larger dispersion in TFP bias than in the main result.

The second main result in figure 8 is that the estimated TFP bias is quantitatively significant. This is summarized in table 2. The table divides firm-year observations into quartile groups based on their CUR and reports the median CUR and TFP bias for each group. For firms in the first quartile, the median CUR is just 27% and the median TFP bias is 1.77, i.e., for the median firm in this group measured TFP that does not account for CUR underestimates the 'true' TFP by 77%. For firms in the second quartile, the median CUR is 52% and the TFP bias is 37%. In the third quartile, the median CUR and TFP bias are 75% and 19%, respectively. The median firm the top quartile has CUR of 100%, and the corresponding TFP bias is small (6%). Overall, for the median firm in the Ethiopian data, CUR is 65% and TFP bias is 25%.

Next, we explore how TFP bias and CUR are related over time. To do so, we aggregate TFP bias across firms in each year using the firms' sales as weight and plot that against average CUR. We present the time-series plot of aggregate TFP bias and aggregate CUR in figure 9. The figure clearly shows that the aggregate TFP bias and aggregate CUR move in the opposite direction. During years of high average CUR (2008, 2010, and 2014), when average CUR is about 80%, aggregate TFP bias is at its lowest and is just over 1.2 (20% bias). During the early years of the sample period and in 2016, average CUR is at its lowest (just over 65%) and the aggregate TFP bias during these period was about 50%.

Bias in output elasticity: We have shown that the bias in measured TFP that does not account for CUR is quantitatively significant, particularly for firms with lower CUR. We now turn to the bias in output elaticities when production function is estimated without accounting for CUR. To do so, we compare output elasticities estimated from equations 8 (which accounts for CUR) and 9 (which does not account for CUR). We estimate these equations using dynamic panel approach.

The results are reported in tables 3 and 4. Table 3 presents results where output elasticities are assumed to be constant across industries. Comparing the estimated output elasticities across the two columns, we see that not accounting for CUR leads to significant underestimation of the coefficient of capital, significant overestimation of the coefficient of labor, and no significant effect on coefficient of material. Theoretically, not accounting for CUR would lead to underestimation of the coefficient of quasi-fixed input (capital) and overestimation of the coefficient of flexible inputs (labor and material) (see appendix A). In view of this, the similarity of the coefficient of material across the two specifications is unexpected. One possible reason is that our estimation assumes constant output elasticities across industries. In table 4 we conduct the estimation for each two-digit industries separately to explore the heterogeneity across industries. The results in this table re-enforce those in table 3 - in 10 out of 12 industries not accounting for CUR leads to significant underestimation of the coefficient of capital and significant overestimation of the coefficient of labor. However, the effect on coefficient of material is not uniform across industries. Not accounting for CUR significantly overestimates the coefficient of material in 4 industries, underestimates the coefficient of material in 1 industry and in the remaining 7 industries the material coefficient remains relatively stable.

5.2 CUR and TFP bias: cross-sectional evidence

WBES data: In our WBES data, we do not observe M^f. As a result, we cannot infer the level of L^f either. However, we observe CUR (i.e. $\frac{Y}{Y^f}$). Thus, we follow a different approach to quantify the bias in measured productivity. Our approach requires constant returns to scale (CRS) assumption. Suppose $U \equiv \frac{Y}{Y^f}$ denotes the capacity utilization rate, i.e., actual output relative to output under full capacity. Starting with equation 8, multiplying both sides by U, and using our CRS assumption, we obtain:

$$\begin{aligned} U_{isc}Y^f_{isc} &= e^{\omega_{isc}+\varepsilon_{isc}}(U_{isc}K^f_{isc})^{\beta_k}(U_{isc}L^f_{isc})^{\beta_l}(U_{isc}M^f_{isc})^{(1-\beta_k-\beta_l)} \\ Y_{isc} &= e^{\omega_{isc}+\varepsilon_{isc}}(U_{isc}K^f_{isc})^{\beta_k}(L_{isc})^{\beta_l}(M_{isc})^{(1-\beta_k-\beta_l)} \end{aligned} \tag{12}$$

where the indices i, s, and c denote firm, two-digit industry/sector, and country. Note that we have used our CRS assumption to replace β_m by $(1-\beta_k-\beta_l)$. The second line of the equation makes use of $U_{isc}Y^f_{isc} \equiv Y_{isc}$ is the observed level of output, $U_{isc}L^f_{isc} \equiv L_{isc}$ is the observed level input, and $U_{isc}M^f_{isc} \equiv M_{isc}$ is the observed material input. Note that $U_{isc}K^f_{isc} \equiv K_{isc}$ is the utilized level of capital (not directly observable, but inferred from measures of U and K^f). Estimation of equation 12 gives unbiased measure of TFP. Comparing equation 12 against CRS version of equation 9 (i.e $Y_{isc} = e^{\tilde{\omega}_{isc}+\varepsilon_{isc}}(K^f_{isc})^{\alpha_k}(L_{isc})^{\alpha_l}(M_{isc})^{1-\alpha_k-\alpha_l}$), the difference is the measure of capital. Equation 9 assumes the available capital is fully utilized whereas equation 12 adjusts the capital level to obtain the utilized level of capital. Because of these differences, the output elasticities and the implied TFPs will be different across the two specifications. To see this more clearly, take logs of both equations:

$$y_{isc} = \alpha_k k^f_{isc} + \alpha_l l_{isc} + (1 - \alpha_k - \alpha_l)m_{isc} + \tilde{\omega}_{isc} + \varepsilon^1_{isc} \tag{13a}$$

v.s.

$$y_{isc} = \beta_k k^f_{isc} + \beta_l l_{isc} + (1 - \beta_k - \beta_l)m_{isc} + \beta_k u_{isc} + \omega_{isc} + \varepsilon^2_{isc} \tag{13b}$$

Estimating equation 13a gives TFP measure that does not account for utilization rate of capital, $\tilde{\omega}_{isc}$. Comparing this against equation 13b (ignoring the bias in output elasticities for the moment), $\tilde{\omega}_{isc}$ includes both the true TFP ω_{isc} and the term $\beta_k u_{isc}$. Because u_{isc} is negative and β_k is a positive number, $\tilde{\omega}_{isc}$ underestimates the true TFP ω_{isc}, and the magnitude of the bias increases as CUR decreases.

To estimate the bias in TFP, we follow the same procedure as we followed to estimate equation 11. Taking the differences across equations 13a and 13b and rearranging gives:

$$u_{isc} = \theta_k(k^f_{isc} - m_{isc}) + \theta_l(l_{isc} - m_{isc}) - \frac{1}{\beta_k}\underbrace{(\omega_{isc} - \tilde{\omega}_{isc})}_{\text{TFP bias}} + \varepsilon_{isc} \tag{14}$$

where $u_{isc} = \log(Y_{isc}) - \log(Y^f_{isc})$, $\theta_k \equiv -(\frac{\beta_k - \alpha_k}{\beta_k})$ and $\theta_l \equiv -(\frac{\beta_l - \alpha_l}{\beta_k})$. Because our WBES data is cross-sectional, we estimate equation 14 using OLS to obtain the estimated values of θ_k and θ_l. Given how similar results are across OLS and dynamic panel specifications in estimation of equation 11, we are confident that the use of OLS in estimation of equation 14 is less concerning. We obtain the estimated value of β_k following non-parametric approach and our CRS assumption (see below).

Result. We present the results in figures 10 and 11, and tables 5 and 6. Figure 10 pools together firms from all countries and plots the TFP bias estimated from equation 14 ($\frac{\text{Adjusted TFP}}{\text{Non-adjusted TFP}} = \exp(\omega_{isc} - \tilde{\omega}_{iisc})$) against the firm's CUR. The figure shows striking similarity with similar figure based on our Ethiopian panel data.[10] The figure shows that: (i) TFP bias sharply decreases with firm CUR and converges to 1 as CUR approaches 100%, and (ii) the the level of TFP bias is large. This is summarized in table 5 where firms in the data are grouped into four quartiles based on their CUR. The median firm in the lowest quartile has 50% CUR and the level of TFP bias is 34%. On the contrary, the median firm in the highest quartile has CUR of 100%, and the corresponding TFP bias is negligible (2%).

In figure 11 we aggregate TFP bias at country level using sampling weights[11]

[10] Note that in the WBES, CUR is reported for most firms rounded to the nearest multiple of 5 or 10, hence we see bunching at those values.

[11] Alternatively, using firm sales as weight gives similar conclusion

and plot that against country-level average CUR. The figure shows a clear negative relationship (a correlation of -0.5), implying that TFP bias is significantly higher in countries with lower average CUR.

Finally, we explore how much this TFP bias alters cross-country comparison of TFP. To do so, we first estimate the adjusted TFP using 13b. Because we have only cross-section data in WBES, we cannot consistently estimate the production function parameters in equation 13b. We thus follow a non-parametric approach to obtain the production function coefficients and TFP in equation 13b. Specifically, we estimate the coefficients of labor and material as the median labor and material share in firm revenue in each industry-country cell and rely on our CRS assumption to infer the coefficient of capital as $\beta_k = 1 - \beta_l - \beta_m$. Hsieh and Klenow (2009) employ this approach to estimate TFP in their analysis.[12] We use these parameter values in equation 13b to recover the measure of TFP that accounts for CUR (adjusted TFP). We then infer the non-adjusted TFP using the adjusted TFP and our estimated TFP bias.

We report the median values of adjusted and non-adjusted TFP together with the median CUR for countries in four income groups based on GDPPC in 2010 USD: low-income (GDPPC of below \$1035), lower middle-income (GDPPC \$1035-\$4045), upper middle-income (GDPPC \$4046-\$12535), and high-income (GDPPC higher than \$12536). The result is reported in table 6. Focusing on TFP gap between low- and high-income countries, we see that adjusted TFP in high-income countries is 2.75 times that of low-income countries.[13] On the other hand, the non-adjusted TFP of high-income countries is 3.90 times that of low-income countries. That is, the TFP gap based on non-adjusted TFP measure exaggerates the TFP gap between high- and low-income countries by about 40%. Similar conclusions hold when comparing adjusted and non-adjusted TFP gaps between low- and middle-income, and between high-and middle-income countries, i.e., TFP that does not account for CUR significantly overestimates the TFP gap. This exercises suggests that a non-negligible fraction of measured TFP gap between high- and low-income countries can be attributed to lower CUR in low-income countries compared to high-income countries.

6 Conclusions

A growing literature over the last decade explores factors that explain the wide TFP gap between advanced and developing countries. The most influential branch of this literature focuses on the role of policies and institutions that lead to within-industry

[12] See Blackwood et al. (2021) for more discussion.

[13] To obtain this: $\frac{\text{TFP}_{\text{high income}}}{\text{TFP}_{\text{low income}}} = \exp(3.58 - 2.57) = 2.75$

misallocation of factors across firms in driving aggregate TFP down, which is widely believed to be particularly more pronounced in developing countries. In this paper we suggest another important factor in explaining TFP gap between poor and rich countries – lower CUR by firms in poor countries compared to their counterparts in rich countries. We base our argument on two findings. First, average firm CUR significantly increases with GDP per capita. Second, measures of TFP that do not account for firm CUR considerably underestimate actual TFP when average CUR is low (such as in poorer countries) but only modestly when average CUR is high (such as in richer countries). These two findings together imply that part of cross-country variation in TFP could be attributed to differences in average CUR than reflecting differences in 'true' productivity. From our estimation, measured TFP that does not account for CUR exaggerates TFP gap between rich and poor countries by over 40%.

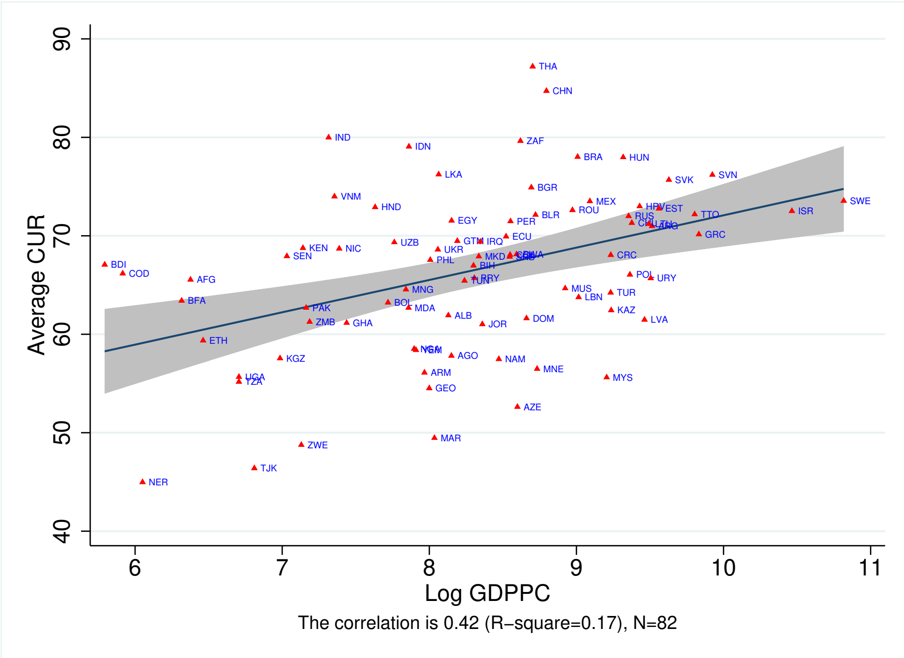
We suggest a theoretical model to explain variation in CUR across firms and countries. In the model, we emphasize the role of supply and demand constraints. We find strong empirical evidence that supply constraints underlie the main reason behind variation in CUR across firms and countries.

Next, we investigate how variation in CUR affects estimation of production function and TFP, which is empirically widely used to measure and compare firm performance within and across countries as well as over time. We show that not accounting for CUR leads to biased estimation of production function parameters and TFP. In particular, we show that in our Ethiopian manufacturing long panel data measures of TFP that do not account for CUR significantly underestimate the true productivity when CUR is low. But when CUR is high enough, such bias is negligible. We also show that similar relationship holds between bias in measured TFP and the average CUR across cross-section of countries.

We believe that the topic of capacity underutilization and its implications for estimation of TFP is not given due attention it deserves in academic research, perhaps due to limited data (most standard firm surveys do not include information about capacity utilization). As such, future research in this area using novel data would be a valuable contribution.

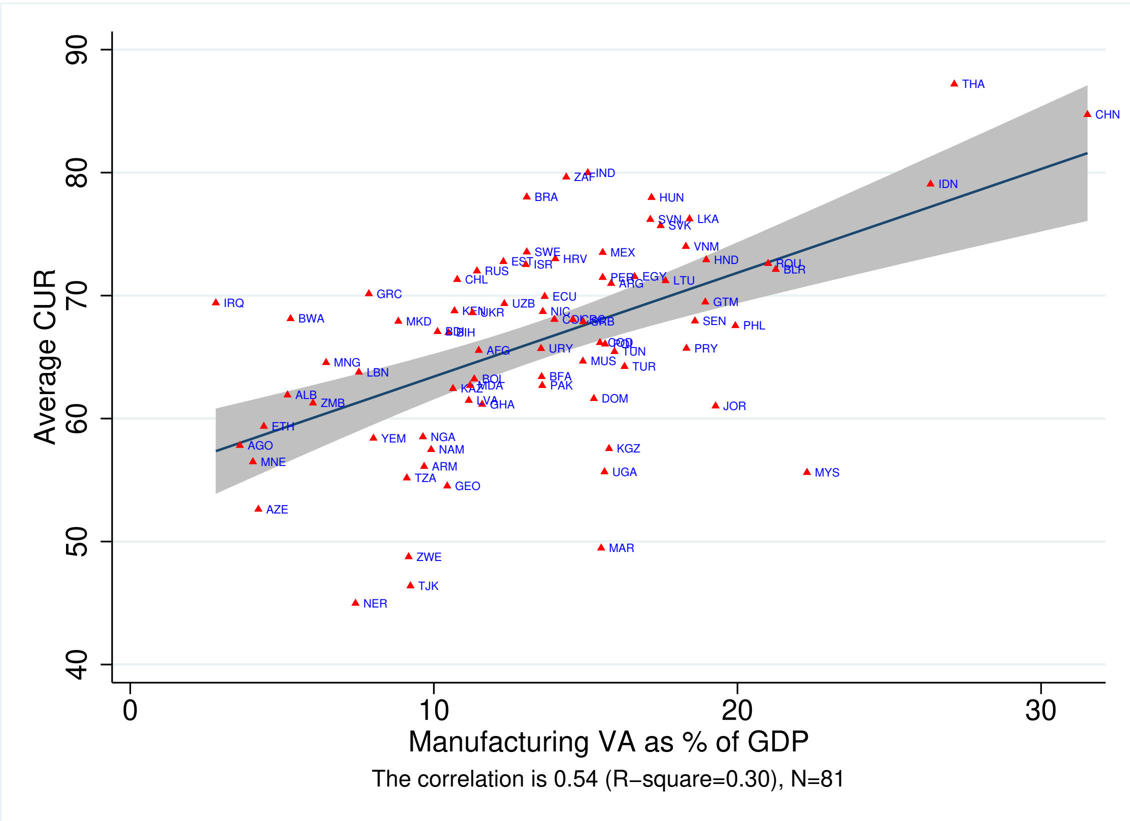
Figures

Figure 1: Average CUR and GDP per capita



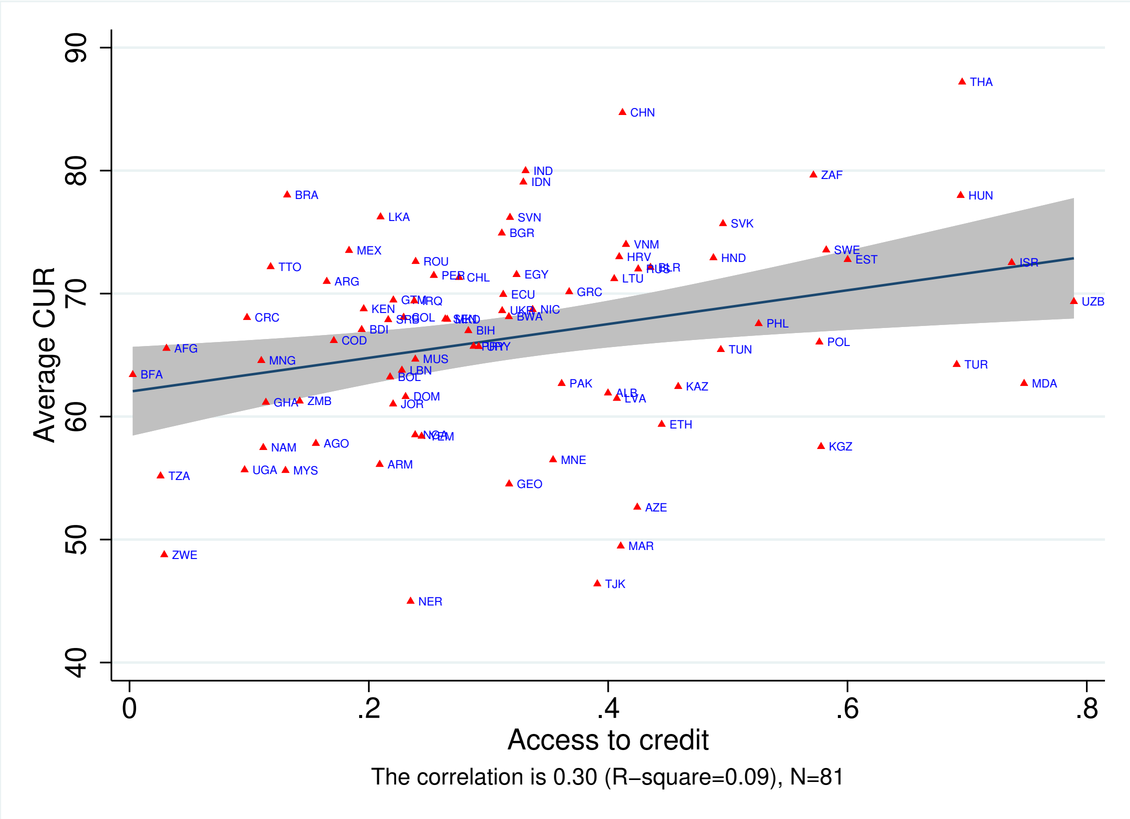
Notes: Aggregate CUR is sales-weighted average capacity utilization across firms in a country.

Figure 2: Domestic manufacturing size and CUR



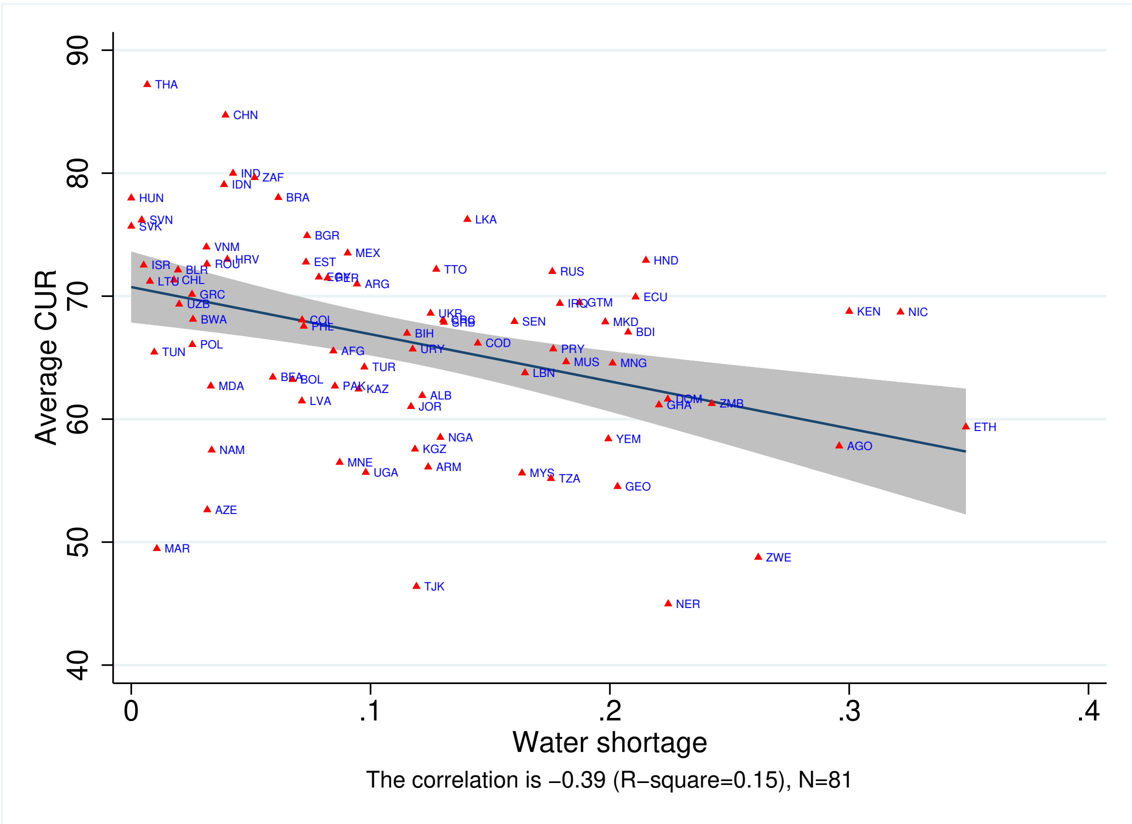
Notes: Aggregate CUR is sales-weighted average capacity utilization across firms in a country. Manufacturing value-added as a percentage of GDP is a measure of the size of manufacturing.

Figure 3: Access to credit and CUR



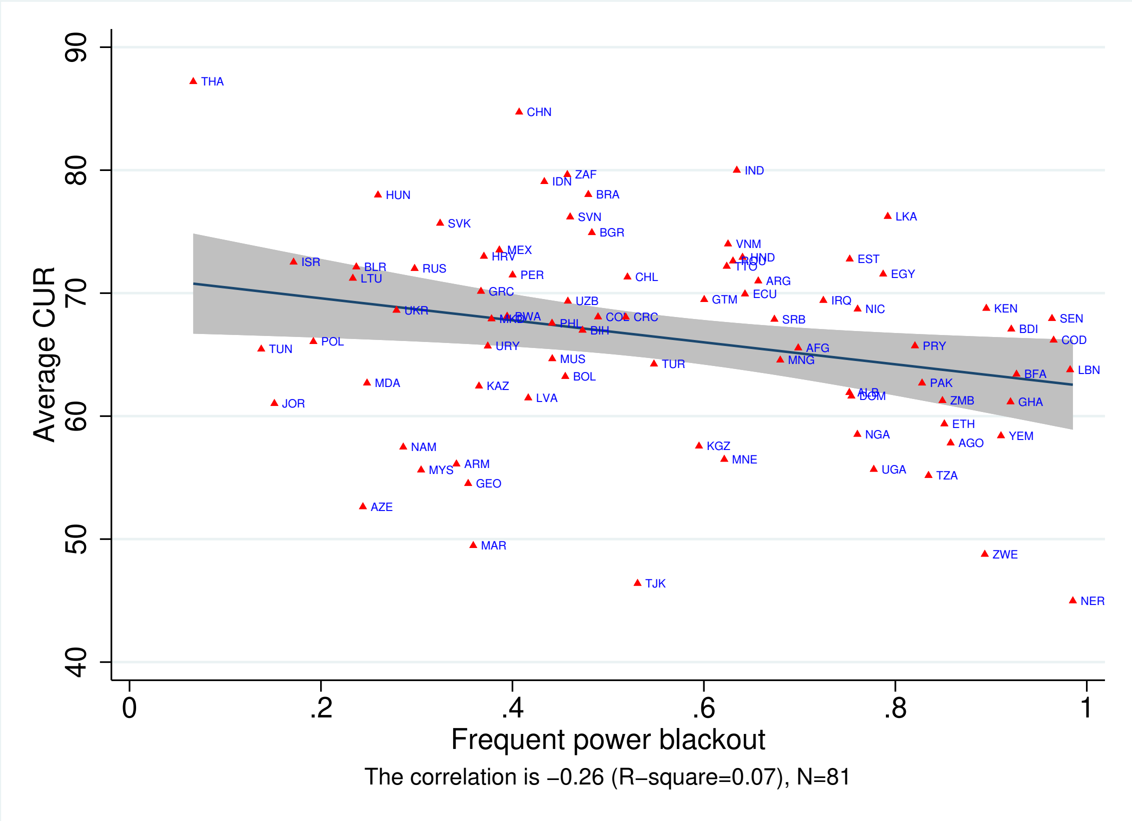
Notes: Aggregate CUR is sales-weighted average capacity utilization across firms in a country. Access to credit is the fraction of firms in a country which report to have access to credit.

Figure 4: Water shortage and CUR



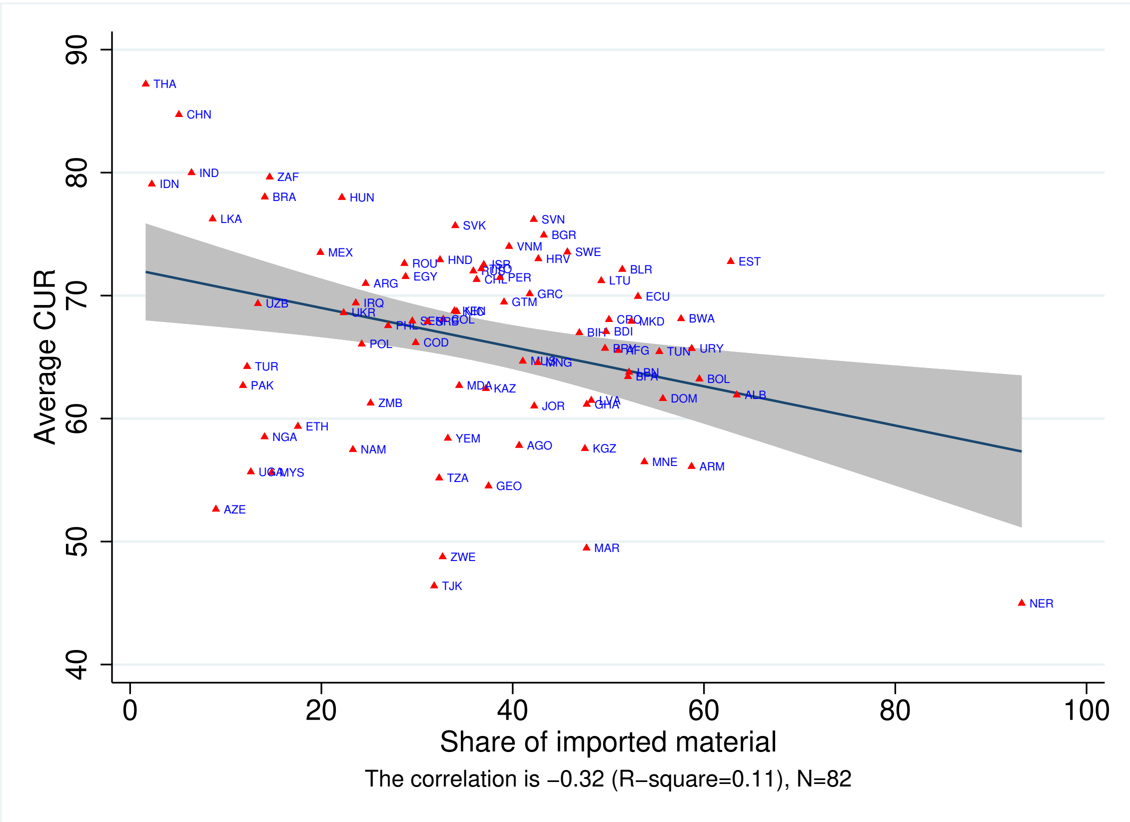
Notes: Aggregate CUR is sales-weighted average capacity utilization across firms in a country. Water shortage is the fraction of firms in the country which report to have experienced a shortage of water that affected their production.

Figure 5: Electricity shortage and CUR



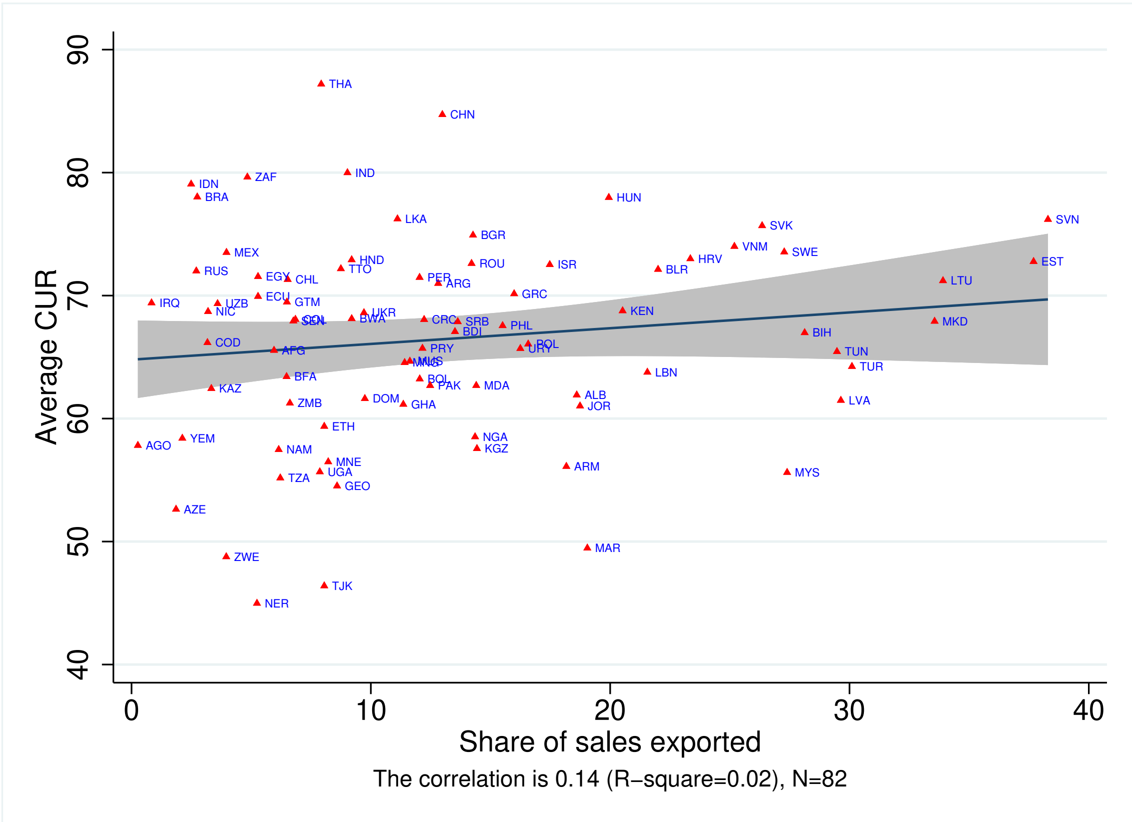
Notes: Aggregate CUR is sales-weighted average capacity utilization across firms in a country. Frequent power blackout is measured as the fraction of firms in the country which have reported to have experienced frequent power outages that disrupted their production.

Figure 6: Share of imported input and CUR



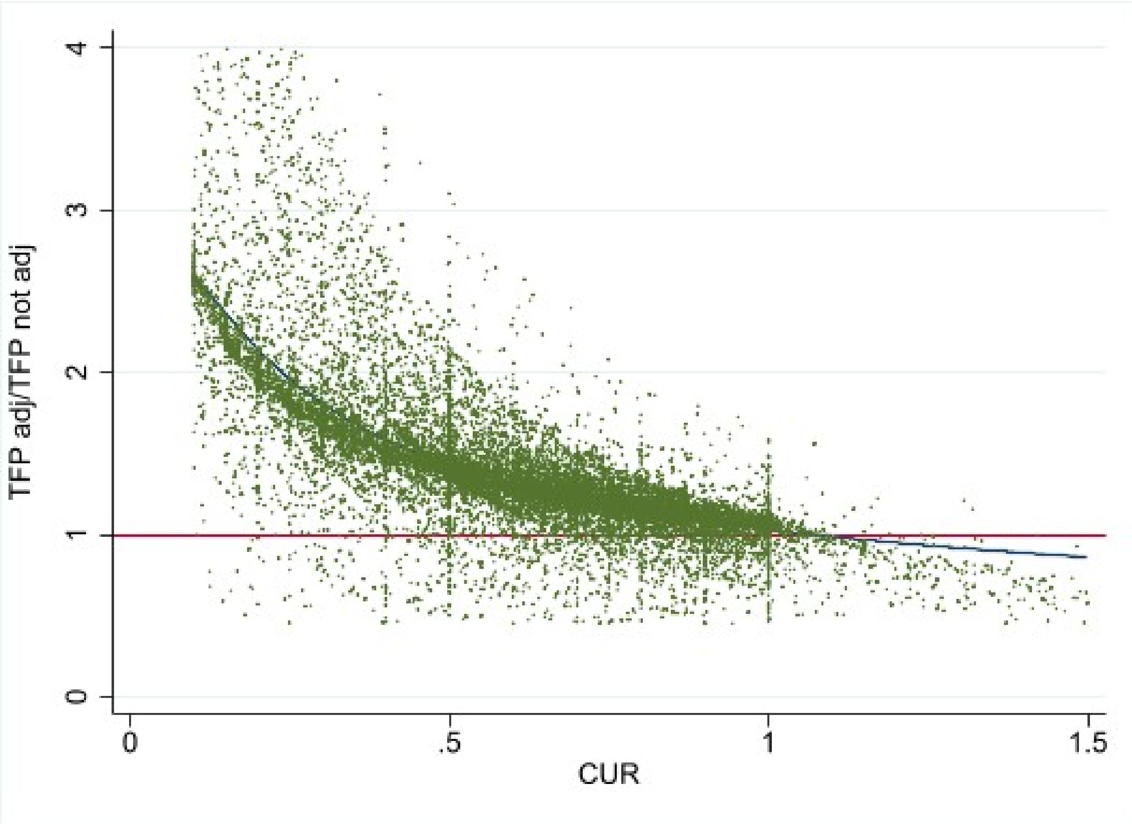
Notes: Aggregate CUR is sales-weighted average capacity utilization across firms in a country. Share of imported input is sales-weighted average share of imports in the firms' material input.

Figure 7: Export orientation and CUR



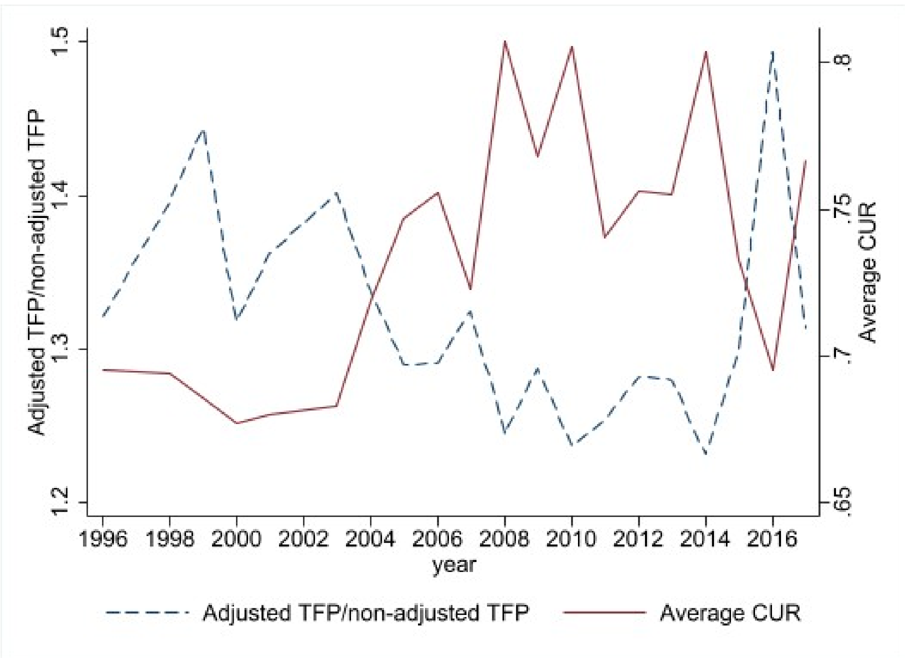
Notes: Aggregate CUR is sales weighted average capacity utilization across firms in a country. Share of sales exported is sales-weighted average share of firm sales exported.

Figure 8: Bias in measured TFP vs CUR: firm-level (Ethiopian panel data)



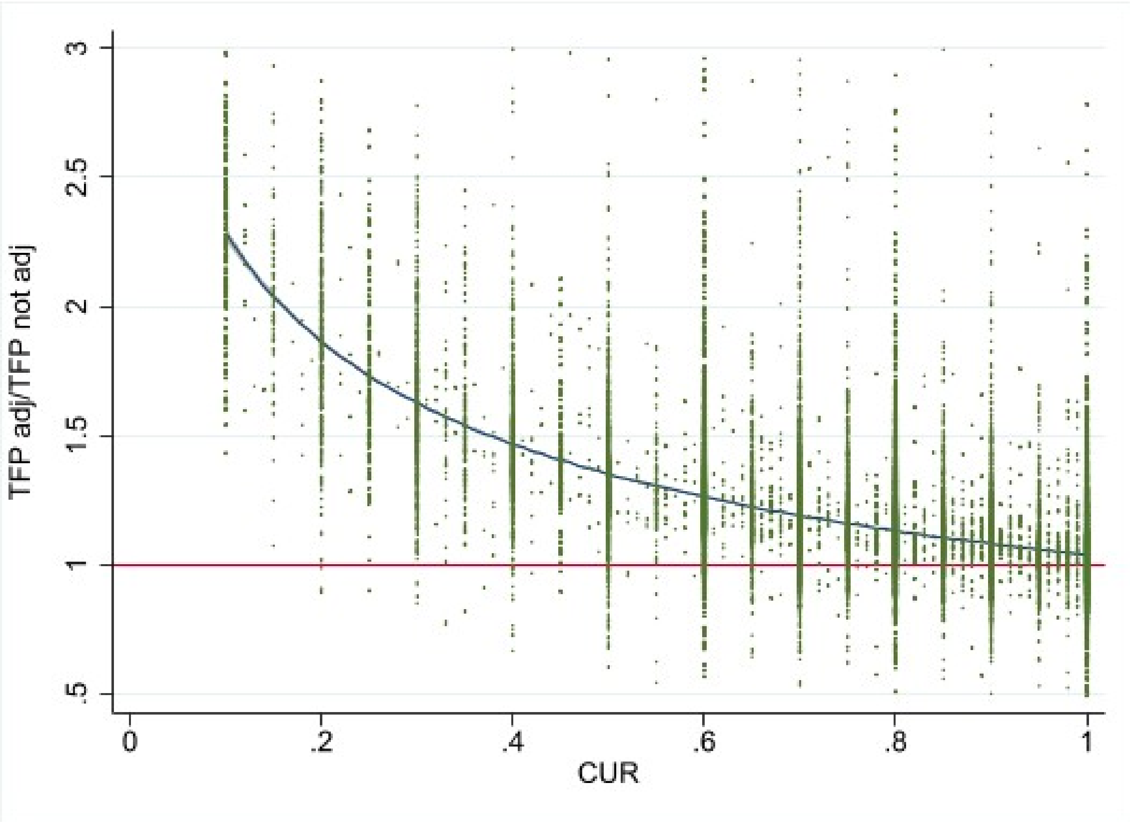
Notes: The vertical axis measures the ratio $\frac{\text{TFP}_{\text{adj}}}{\text{TFP}_{\text{not adj}}}$ and the horizontal axis measures firm CUR. Each dot is firm-year observation.

Figure 9: TFP bias and CUR: time series relationship (Ethiopian panel data



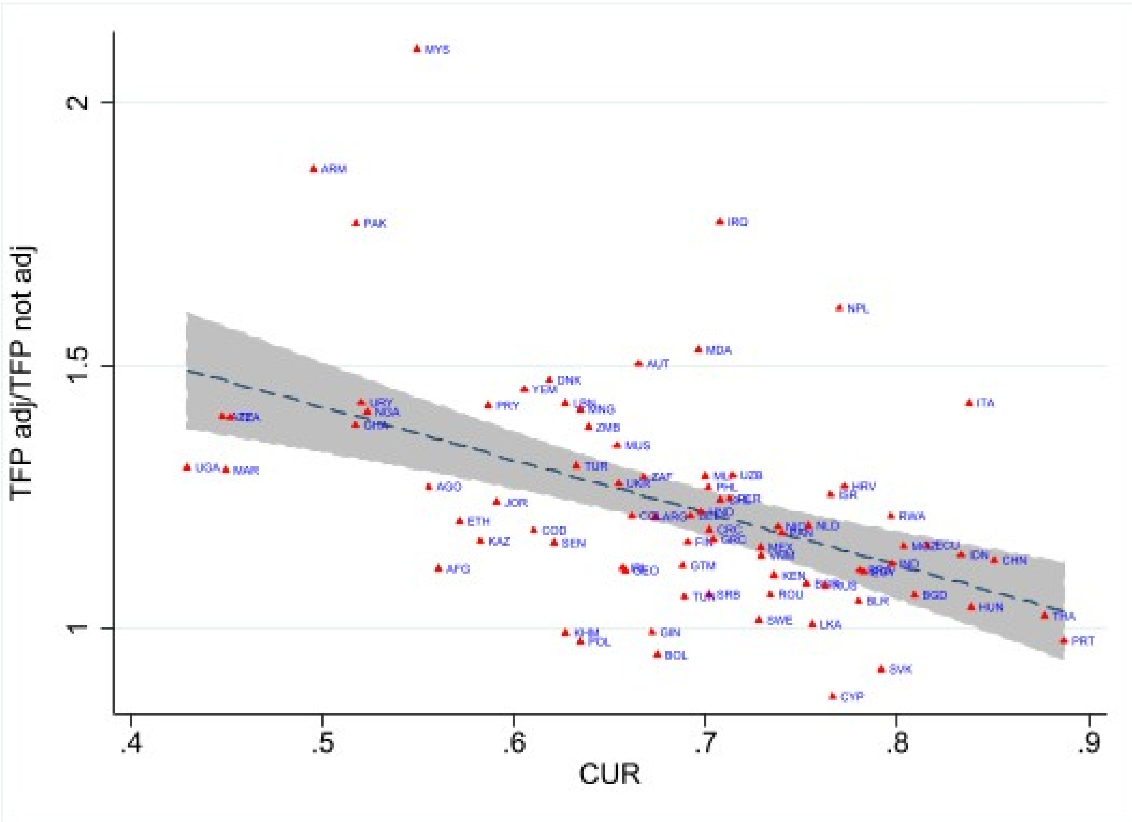
Notes: The left axis measures sales-weighted yearly average TFP bias ($\frac{\text{TFP}_{\text{adj}}}{\text{TFP}_{\text{not adj}}}$) and the right axis measures average CUR.

Figure 10: Bias in measured TFP vs CUR: WBES data



Notes: The vertical axis measures firm level measure of the ratio $\frac{\text{TFP}_{\text{adj}}}{\text{TFP}_{\text{not adj}}}$ and the horizontal axis measures firm CUR. Each dot is a firm in WBES.

Figure 11: Bias in measured TFP vs CUR: WBES data



Notes: The vertical axis measures the average ratio $\frac{\text{TFP}_{\text{adj}}}{\text{TFP}_{\text{not adj}}}$ and the horizontal axis measures the average CUR across firms within a country. Each dot is a country in WBES.

Table 1: Factors affecting capacity utilization

	(1) OLS	(2) Tobit
	Panel A: Demand constraints	
Main market is national market	1.885***	2.199***
	(0.645)	(0.848)
Main market is international market	1.499	2.036*
	(1.024)	(1.095)
Export Share	0.004	0.003
	(0.012)	(0.011)
Log Import penetration	-0.297	-0.362
	(0.205)	(0.236)
Competes with informal sector	-0.417	-0.276
	(0.708)	(1.117)
log Number of direct competitors	0.411**	0.465*
	(0.161)	(0.261)
	Panel B: Supply constraints	
Share of material imported	-0.015**	-0.019***
	(0.007)	(0.006)
Power outage during the year	-1.732***	-2.439***
	(0.585)	(0.683)
Water shortage during the year	-1.938**	-2.342***
	(0.770)	(0.880)
Access to credit	1.929***	2.724***
	(0.404)	(0.494)
	Panel C: Control variables	
Percent of firm owned by foreigner	0.003	0.002
	(0.005)	(0.008)
Percent of firm owned by government	-0.043*	-0.046
	(0.024)	(0.029)
Log GDP PC	19.417***	23.057***
	(4.418)	(5.610)
aged 6-10 years	0.379	0.324
	(0.517)	(0.641)
aged 11-20 years	0.032	-0.259
	(0.536)	(0.617)
aged 21-50 years	-1.958**	-2.793***
	(0.714)	(0.906)
aged 51 or more years	-3.363***	-4.396***
	(0.805)	(1.023)
Medium (20-99 workers)	2.789***	2.822***
	(0.477)	(0.550)
Large (100 or over workers)	6.609***	7.124***
	(0.720)	(0.731)
N	48839	48839
R^2	0.120	

Notes: All regressions include country, industry, and year fixed effects. Standard errors are two-way clustered across ISIC-2digit industries and countries. Openness measures are calculated at ISIC-2digit level. Import openness is calculated as industry import divided by industry output. Export openness is industry export divided by industry output. Small size (<20 workers) dummy is the baseline category. The Tobit regression accounts for truncation at the top (100%) in capacity utilization rate. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Median TFP bias by quartiles of CUR: Ethiopian panel data

	Median CUR	Median TFP bias
First quartile	0.27	1.77
Second quartile	0.52	1.37
Third quartile	0.75	1.19
Fourth quartile	1.00	1.06
Total	0.65	1.25

Notes: This table reports the median CUR and the median TFP bias for firms in different quartiles based on CUR.

Table 3: CU and bias in PF parameters: dynamic panel

	(1)	(2)
	Accounting for CUR (Eq. 8)	Without accounting for CUR (Eq. 9)
Capital	0.059***	0.039***
	(0.005)	(0.005)
Labor	0.098***	0.173***
	(0.011)	(0.011)
Material	0.637***	0.643***
	(0.011)	(0.010)
N	14676	14676
R^2	0.920	0.938

Notes: Robust Standard errors in parenthesis. The regressions in both columns include (four-digit) industry-year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: CU and bias in PF parameters: Industry-level using dynamic panel

	Accounting for CUR (Eq. 8)			W/t accounting for CUR (Eq. 9)		
	Capital	Labor	Material	Capital	Labor	Material
15 (Food and Beverage)	0.058	0.054	0.713	0.019	0.161	0.704
17 (Textiles)	0.088	0.044	0.663	0.038	0.161	0.706
18 (Apparel)	0.027	0.173	0.674	0.057	0.120	0.631
19 (Leather)	0.070	0.117	0.580	0.028	0.142	0.606
20 (Wood)	0.043	0.232	0.579	0.038	0.343	0.594
21 (Paper)	0.073	0.117	0.740	0.052	0.227	0.797
22 (Printing)	0.091	0.137	0.566	0.034	0.242	0.588
25 (Rubber and plastic)	0.063	0.108	0.578	0.066	0.207	0.577
26 (Non-metallic mineral)	0.091	0.212	0.495	0.081	0.270	0.502
27 (Basic metals)	0.078	0.137	0.757	0.043	0.071	0.818
28 (Fabricated Metal)	0.117	0.002	0.641	0.097	0.153	0.655
36 (Furniture)	0.034	0.103	0.674	0.030	0.135	0.687

Notes: This table reports production function parameters estimated using dynamic panel approach, accounting for CUR (Equation 8) and without accounting for CUR (Equation 9) for each two-digit industry separately. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Median TFP bias by quartiles of CUR: WBES

	Median CUR	Median TFP bias
1-First quartile	0.50	1.34
2-Second quartile	0.75	1.13
3-Third quartile	0.90	1.07
4-Fourth quartile	1.00	1.02
Total	0.80	1.12

Notes: This table reports the median CUR and the median TFP bias for firms in different quartiles based on CUR.

Table 6: Aggregate TFP and CUR across country income groups: WBES

	Adjusted lnTFP	Non-adjusted lnTFP	CUR
1-Low-income	2.57	2.35	0.64
2-Lower middle-income	2.42	2.11	0.66
3-Upper middle-income	2.81	2.64	0.70
4-High-income	3.58	3.71	0.73

Notes: This table reports average CUR and average lnTFP (with and without accounting for CUR) for countries in different income groups. The four income groups are defined as follows: low-income (GDPPC of below \$1035), lower middle-income (GDPPC \$1035-\$4045), upper middle-income (GDPPC \$4046-\$12535), and high-income (GDPPC higher than \$12536).

Appendix A Direction of bias in production function parameters

When firms operate below full capacity due to constraints in the flexible input market, estimation of production function without accounting for CUR would lead to downward bias in the coefficient of quasi-fixed input (capital) and upward bias in the coefficient of flexible input (labor and capital).

To illustrate the effect on coefficient of capital in the simplest possible way, we drop other production factors (labor and capital) and also abstract from unobserved productivity. Let y_{it} is log of the observed output, which is a function of effectively utilized capital k_{it}. Thus the correct estimation equation is given as

$$y_{it} = \beta_k k_{it} + \varepsilon_{it} \tag{15}$$

where ε_{it} is a random measurement error. If the econometrician observes k_{it}, estimation of 15 gives unbiased estimator of β_k. Unfortunately the econometrician cannot observe k_{it}. Instead, the econometrician observes the firm's book value of capital k_{it}^f which is related to the effectively utilized capital as $k_{it}^f = k_{it} - u_{it}$ where u_{it} is log of the capital utilization rate. Assume that u_{it} satisfies the property of classic measurement error (i.e., it is uncorrelated with the true independent variable k_{it} and ε_{it}). Under these assumptions, the estimated parameter by the econometrician is given by:

$$\begin{aligned} \hat{\beta}_k &= \frac{\mathrm{Cov}\Big(\beta_k k_{it} + \varepsilon_{it}, k_{it} - u_{it}\Big)}{\mathrm{Var}(k_{it} - u_{it})} \qquad (16) \\ &= \beta_k \frac{\sigma_k^2}{\sigma_k^2 + \sigma_u^2} \qquad (17) \end{aligned}$$

where $\sigma_k^2 = \mathrm{var}(k_{it})$ and $\sigma_u^2 = \mathrm{var}(u_{it})$. Thus, capacity underutilization would lead to attenuation bias to the coefficient of capital.[14]

[14] An alternative argument goes as follows. Consider the case where firms operate in a competitive product market and have a Cobb-Douglas technology. Under these assumptions, output elasticity of an input is equal to the input's income share. Suppose β_k is the true output elasticity of capital (i.e, the capital share of income when production is not constrained). Thus, it satisfies that $\beta_k \frac{PY^f}{K^f} = r$ which implies $\beta_k = \frac{rK^f}{PY^f}$, where Y^f is unconstrained optimal output and r is the rental rate of capital. When a firm is constrained in material input and capital is chosen before the firm observes the constraint, output elasticity with respect to capital is no longer equal to the capital share of income, i.e., there is a wedge x between value of marginal product of capital and the market rental rate: $\alpha_k \frac{PY}{K^f} = r - x$ or $\alpha_k = \frac{rK^f}{PY} - \frac{xK^f}{PY} = \left[\beta_k - \frac{xK^f}{PY^f}\right]\frac{Y^f}{Y}$, where α_k is output elasticity of capital under material constraint, Y is optimal output under binding material constraint and $0 < x < r$. As $Y \longrightarrow Y^f$, $x \longrightarrow 0$, $\alpha_k \longrightarrow \beta_k$. As $x \longrightarrow r$, $\alpha_k \longrightarrow 0$. The capital coefficient in the constrained optimal output underestimates the true capital coefficient. Intuitively, binding material constraints make output less responsive to the quasi-fixed inputs.

The direction of bias in the output elasticity with respect to flexible inputs is the opposite. We illustrate this for labor (by dropping material for the moment). The argument for the coefficient of material is very similar. Also, let's ignore the unobserved productivity for the moment. Let u_{it} is the log of the utilization rate of capital and ε_{it} is a random output measurement error . The correct estimation equation to identify the true production function parameters is as follows:

$$y_{it} = \beta_k k^f_{it} + \beta_k u_{it} + \beta_l l_{it} + \varepsilon_{it} \tag{18}$$

However, an econometrician who does not observe u_{it} estimates the following regression:

$$y_{it} = \alpha_k k^f_{it} + \alpha_l l_{it} + \epsilon_{it} \tag{19}$$

where $\epsilon_{it} = \beta_k u_{it} + \varepsilon_{it}$. The estimated coefficient of labor satisfies:

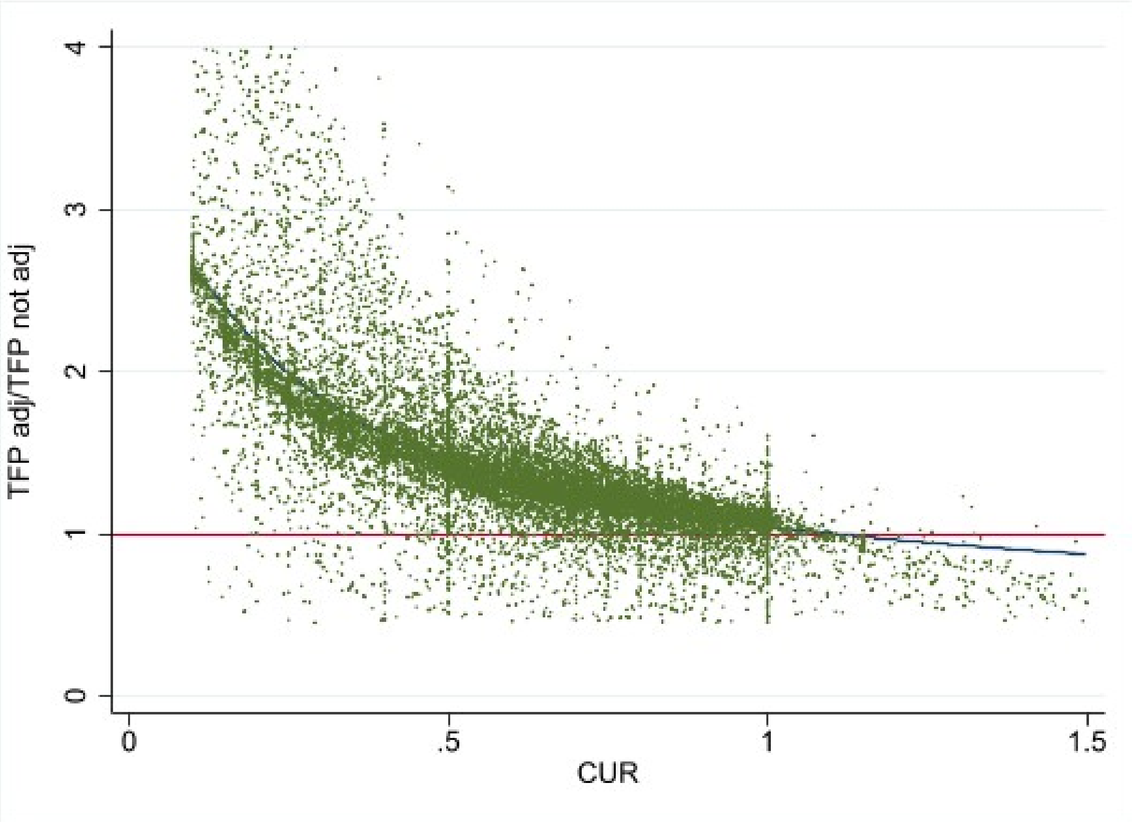
$$\alpha_l = \frac{\mathrm{cov}\Big(y_{it}, l_{it}\Big)}{\mathrm{var}\Big(l_{it}\Big)} \tag{20}$$

$$= \frac{\mathrm{cov}\Big(\beta_k k^f_{it} + \beta_k u_{it} + \beta_l l_{it} + \varepsilon_{it}, l_{it}\Big)}{\mathrm{var}\Big(l_{it}\Big)} \tag{21}$$

Assuming k^f and l are uncorrelated, we have $\alpha_l = \beta_l + \beta_k \frac{\mathrm{cov}(u_{it}, l_{it})}{\mathrm{var}(l_{it})}$. Since $\mathrm{cov}(u_{it}, l_{it}) > 0$ (i.e., the higher the CUR, the higher the employment of labor), α_l overestimates the true output elasticity of labor, β_l.

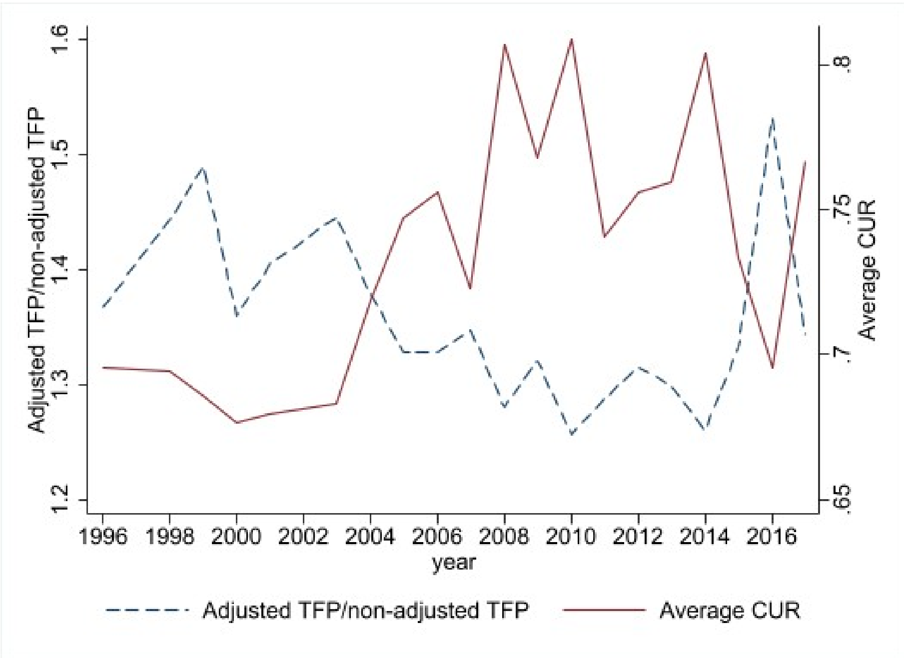
Appendix B Robustness: OLS and industry-level dynamic panel estimation using Ethiopian panel

Figure A.1: Bias in measured TFP vs CUR: firm level (Ethiopian data) - OLS



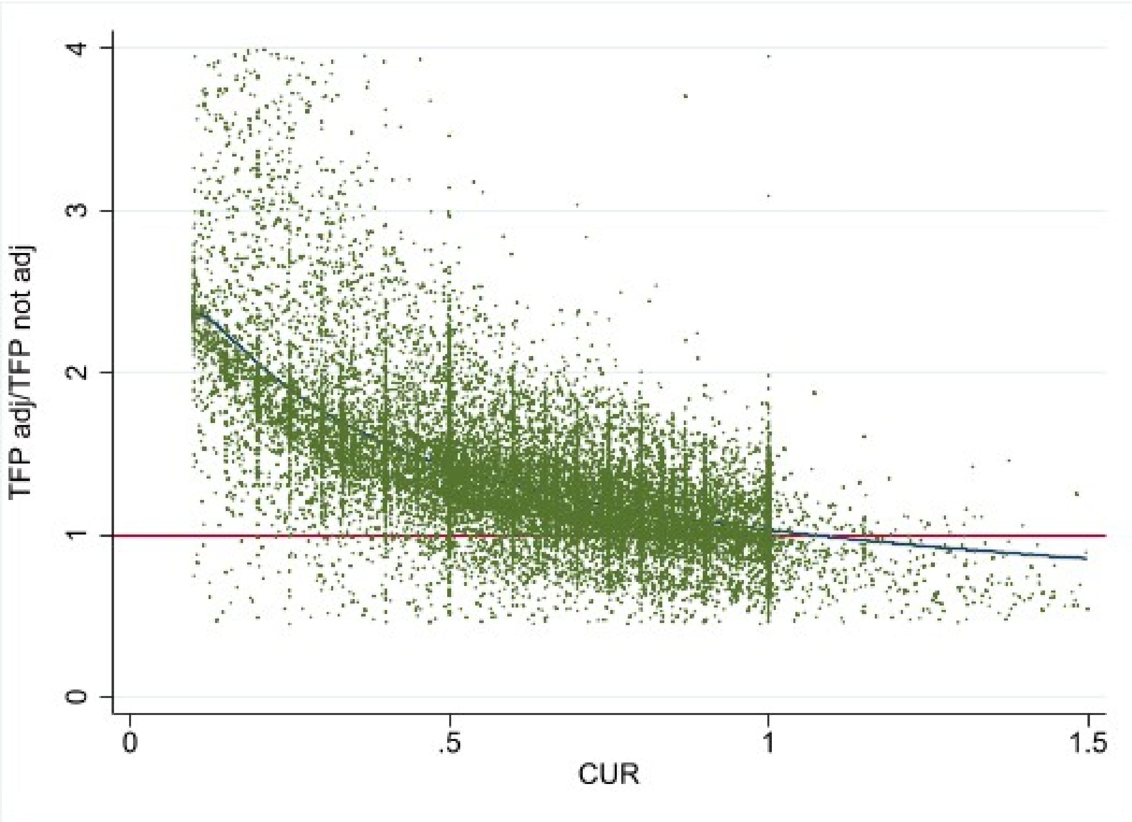
Notes: The vertical axis measures the ratio $\frac{\text{TFP}_{\text{adj}}}{\text{TFP}_{\text{not adj}}}$ whereas the horizontal axis measures. Each dot is firm-year observation. TFP bias is obtained from OLS estimation of equation 11.

Figure A.2: TFP bias and CUR: time series relationship based on panel data from Ethiopia - OLS



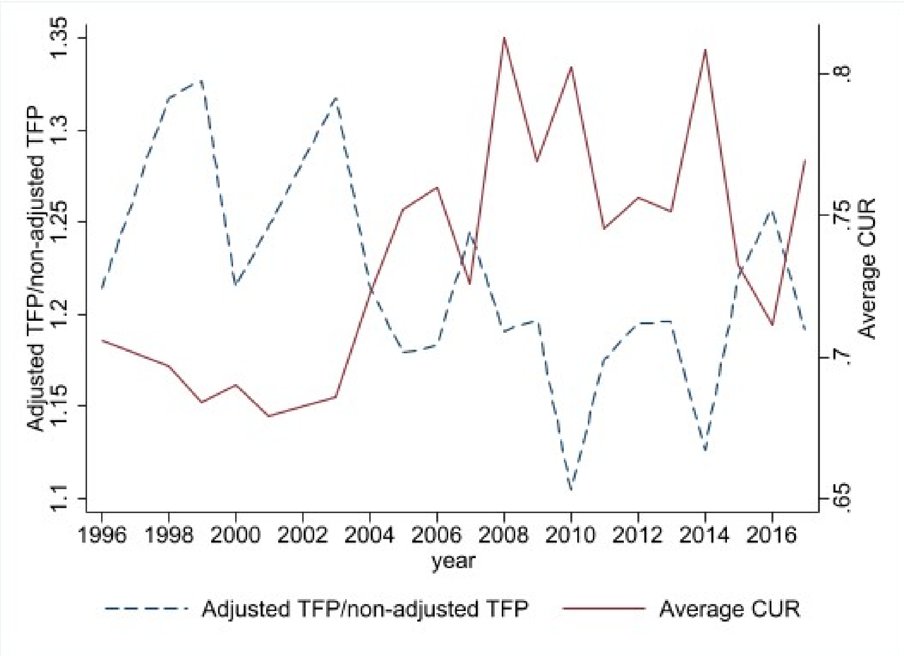
Notes: The left axis measures sales-weighted yearly average TFP bias ($\frac{\text{TFP}_{\text{adj}}}{\text{TFP}_{\text{not adj}}}$) and the right axis measures average CUR. Firm-level TFP bias is obtained from OLS estimation of equation 11.

Figure A.3: Bias in measured TFP vs CUR: firm level (Ethiopian data) - Industry level estimation (dynamic panel)



Notes: The vertical axis measures the ratio $\frac{\text{TFP}_{\text{adj}}}{\text{TFP}_{\text{not adj}}}$ whereas the horizontal axis measures firm CUR. Each dot is firm-year observation. TFP bias is estimated using dynamic panel method separately for each industry.

Figure A.4: TFP bias and CUR: time series relationship based on panel data from Ethiopia - - Industry level estimation (dynamic panel)



Notes:The left axis measures sales-weighted yearly average TFP bias ($\frac{\text{TFP}_{\text{adj}}}{\text{TFP}_{\text{not adj}}}$) and the right axis measures average CUR. Firm-level TFP bias is obtained from estimation of equation 11 using dynamic panel method for each two-digit industry separately.

Appendix C Robustness: Quasi-fixed labor

In our main analysis, we assumed that capital is quasi-fixed input where as labor and material are fully flexible. While these are standard assumptions in estimation of production function, it can be argued that the treatment of labor as a fully flexible input may not accurately capture the reality that firms face in many contexts. On one hand, it is likely that firms are able to adjust the intensive margin of employment (hours worked for workers who are already employed) in the short term. On the other hand, in less flexible labor markets, hiring and firing costs could be significant and firms may not be able adjust the extensive margin of labor (the number of employees) instantaneously. Hence, the treatment of labor as fully flexible input is somewhat controversial.

In this section, we explore the robustness of our main results to treating labor as quasi-fixed input similar to capital. We maintain our assumption that material is fully flexible. The main implication of treating labor as quasi-fixed input together with capital is that when firms face binding constraints in the material input or other flexible inputs such as electricity, they may end up under-utilizing their capital as well as labor inputs (the quasi-fixed inputs). That is, the utilized level of labor input might as well be different from the one observed by statisticians. The effect of this on measured productivity of firms is similar to that of capital underutilization. Firms that face stringent constraints in the flexible input markets will have lower utilization rate of labor and capital and their measured productivity would underestimate their true productivity because the econometrician assumes as if the observed labor and capital were fully employed.

A Ethiopian panel data

We first demonstrate how the treatment of labor as quasi-fixed input affects the estimation of TFP bias using our Ethiopian data. When labor is considered as quasi-fixed input, equations 8 and 9 in the main text are modified as:

$$Y_{it}^{f} = e^{\omega_{it}+\varepsilon_{it}}(K_{it}^{f})^{\beta_k}(L_{it}^{f})^{\beta_l}(M_{it}^{f})^{\beta_m} \tag{22a}$$

$$Y_{it} = e^{\tilde{\omega}_{it}+\varepsilon_{it}}(K_{it}^{f})^{\alpha_k}(L_{it}^{f})^{\alpha_l}(M_{it})^{\alpha_m} \tag{22b}$$

where Y^f, K^f, L^f, M^f are, respectively, output/revenue, capital, labor and material if the plant operates with its full production capacity and equation 22a represents production function when the firm is operating at full capacity production. The econometrician observes $\{Y, K^f, L^f, M\}$ and estimates equation 22b, erroneously assuming that K^f, L^f were fully employed. The bias in TFP from estimating equation

22b instead of 22a can be estimated from the following equation (which is a modified version of equation as:

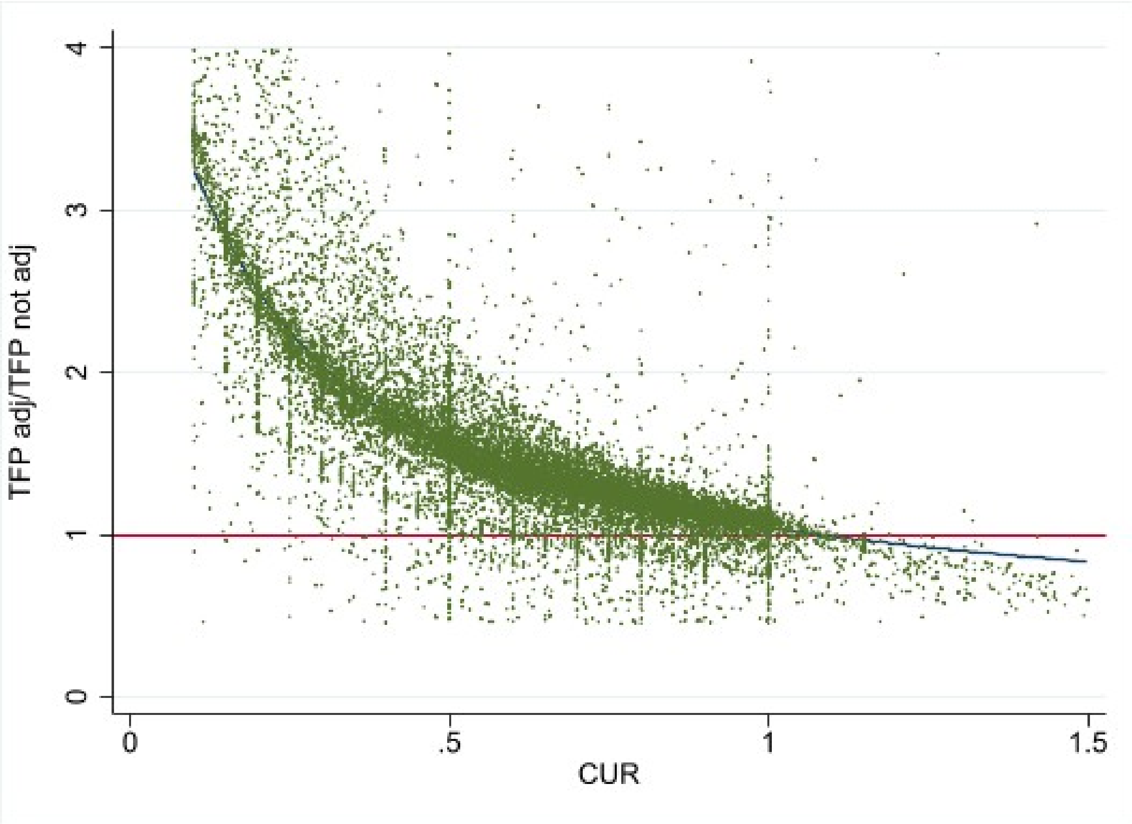
$$y_{it} - y_{it}^f = \gamma_0 + (\alpha_k - \beta_k)k_{it}^f + (\alpha_l - \beta_l)l_{it}^f + \alpha_m m_{it} - \beta_m m_{it}^f - \underbrace{(\omega_{it} - \tilde{\omega}_{it})}_{\text{TFP bias}} + \varepsilon_{it} \quad (23)$$

Given our assumption that the observed levels of capital and labor are K^f and L^f, and given our data on observed and counterfactual (full employment) levels of output and material input (i.e.,{ Y, M, Y^f, M^f}), the above equation can be directly estimated to identify the TFP bias. We follow a procedure similar to the one in our main analysis to estimate the TFP bias.

The results are shown in figure A.5 and A.6 and table A.1. Figure A.5 plots firm-level TFP bias ($\frac{\text{TFP}_{\text{adj}}}{\text{TFP}_{\text{not adj}}}$) against firm CUR. Each dot in the figure represents firm-year observation and the fitted line is fractional-polynomial fitting with 95% confidence interval. The figure is very similar to the main result in figure 8, and it shows that measured TFP that does not account for underutilization of labor and capital significantly underestimates the true productivity for firms with lower CUR. The bias is larger for firms with lower end of CUR and is insignificant for firms at full capacity production. Table A.1 divides firms into four quartiles of CUR and presents median TFP bias for firms in each quartile. Comparing this table against its counterpart in the main result (table 2), it can be seen that treating labor as quasi-fixed input implies larger TFP bias. Intuitively, treating labor as quasi-fixed input allows for potential underemployment of labor while treating labor as fully flexible does not. If labor is indeed fully flexible, there should not be underemployment and the two approaches should imply the same level of TFP bias. Thus, the higher TFP bias obtained under quasi-fixed labor assumption implies that labor is likely to be underemployed, measure of TFP that do not account for such underemployment underestimate the true productivity, similar to the case of capital.

In figure A.6, we aggregate firm-level observations to explore the time-series relation ship between average TFP bias and average CUR. Again, this figure is similar to the one in our main result and shows that the bias in TFP is higher (lower) during years of lower (higher) average CUR.

Figure A.5: Bias in measured TFP vs CUR: firm-level (Ethiopian panel data) - quasi-fixed labor



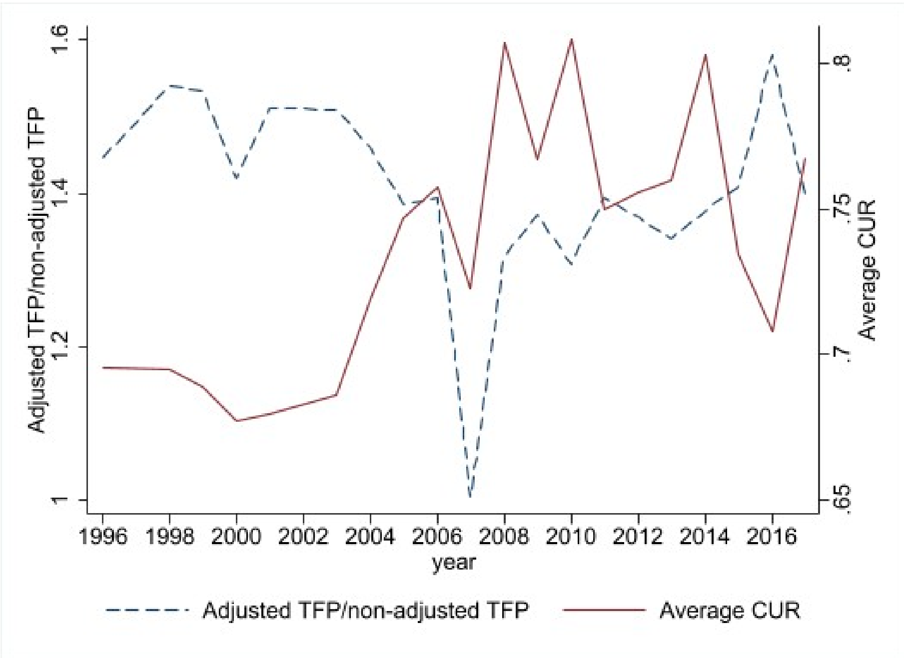
Notes: The vertical axis measures the ratio $\frac{\text{TFP}_{\text{adj}}}{\text{TFP}_{\text{not adj}}}$ and the horizontal axis measures firm CUR. Each dot is firm-year observation.

Table A.1: Median TFP bias by quartiles of CUR: Ethiopian panel data (quasi-fixed labor)

	Median CUR	Median TFP bias
1-First quartile	0.27	2.06
2-Second quartile	0.52	1.49
3-Third quartile	0.75	1.24
4-Fourth quartile	1.00	1.07
Total	0.65	1.32

Notes: This table reports the median CUR and the median TFP bias for firms in different quartiles based on CUR.

Figure A.6: TFP bias and CUR: time series relationship (Ethiopian panel data) - quasi-fixed labor



Notes: The left axis measures sales-weighted yearly average TFP bias ($\frac{\text{TFP}_{\text{adj}}}{\text{TFP}_{\text{not adj}}}$) and the right axis measures average CUR.

B WBES data

When labor is considered as quasi-fixed input, the utilized level of labor differs from the observed level of labor, just like capital. The econometrician estimates the following equation

$$Y_{isc} = e^{\tilde{\omega}_{isc}+\varepsilon_{isc}}(K^f_{isc})^{\alpha_k}(L^f_{isc})^{\alpha_l}(M_{isc})^{(1-\alpha_k-\alpha_l)} \tag{24}$$

which assumes that the available levels of capital and labor are fully utilized. The correct estimation equation, which is a modified version of equation 12, is as follows:

$$Y_{isc} = e^{\omega_{isc}+\varepsilon_{isc}}(U_{isc}K^f_{isc})^{\beta_k}(U_{isc}L^f_{isc})^{\beta_l}(M_{isc})^{(1-\beta_k-\beta_l)} \tag{25}$$

Given data on U, we can infer the utilized levels of capital and labor (i.e. $\{U_{isc}K^f_{isc}, U_{isc}L^f_{isc}\}$), and estimate 25 to identify the correct level of productivity.

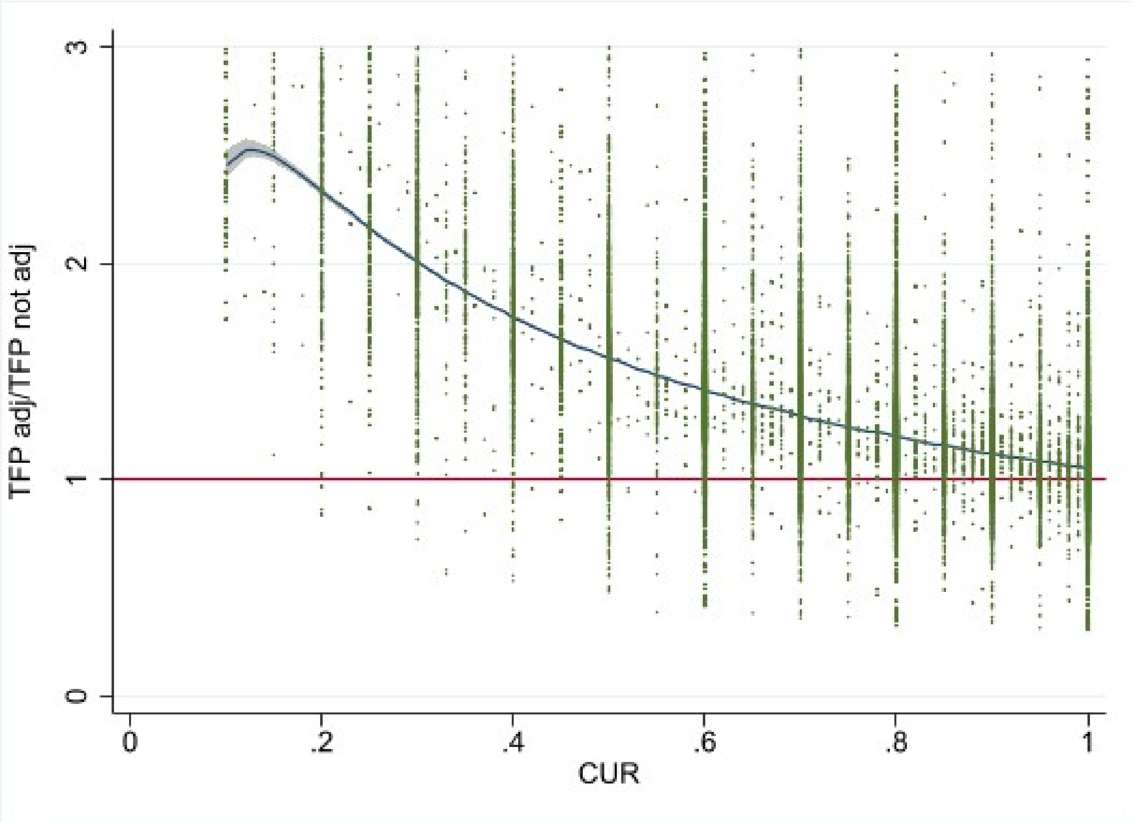
Following similar procedure as in our main analysis, we estimate the bias in measured TFP due to estimation of equation 24 instead of 25, from the following equation:

$$u_{isc} = \frac{(\alpha_k-\beta_k)}{(\beta_k+\beta_l)}(k^f_{isc}-m_{isc}) + \frac{(\alpha_l-\beta_l)}{(\beta_k+\beta_l)}(l^f_{isc}-m_{isc}) - \frac{1}{\beta_k+\beta_l}\underbrace{(\omega_{isc}-\tilde{\omega}_{isc})}_{\text{TFP bias}} + \varepsilon_{isc} \tag{26}$$

Notice that this equation is just a slightly modified version of equation 14. We follow similar procedure as in main analysis to estimate equation 26 and identify the TFP bias.

The result is shown in figure A.7 and table A.2. Comparing these results against their counterparts in figure 10 and table 5, it can be seen that the results are comparable. However, similar to the results based on Ethiopian panel data, the treatment of labor as quasi-fixed input implies slightly larger estimate of TFP bias than when labor is treated as quasi-fixed.

Figure A.7: Bias in measured TFP vs CUR: WBES data



Notes: The vertical axis measures firm level measure of the ratio $\frac{\text{TFP}_{\text{adj}}}{\text{TFP}_{\text{not adj}}}$ and the horizontal axis measures firm CUR. Each dot is a firm in WBES.

Table A.2: Median TFP bias by quartiles of CUR: WBES (quasi-fixed labor)

	Median CUR	Median TFP bias
1-First quartile	0.50	1.57
2-Second quartile	0.75	1.21
3-Third quartile	0.90	1.10
4-Fourth quartile	1.00	1.04
Total	0.80	1.19

Notes: This table reports the median CUR and the median TFP bias for firms in different quartiles based on CUR.

Table A.3: CUR, TFP and firm exit: evidence from Ethiopia

	Industry fixed effects			Firm fixed effects		
	exit	exit	exit	exit	exit	exit
CUR standardized	-0.028***		-0.023***	-0.010***		-0.008***
	(0.004)		(0.004)	(0.003)		(0.003)
TFP standardized		-0.027***	-0.022***		-0.018**	-0.016**
		(0.005)	(0.005)		(0.007)	(0.007)
Medium (20-99 workers)	-0.088***	-0.094***	-0.088***	-0.034**	-0.041***	-0.040***
	(0.008)	(0.010)	(0.009)	(0.013)	(0.013)	(0.013)
Large (100 or over workers)	-0.127***	-0.144***	-0.131***	-0.049***	-0.064***	-0.061***
	(0.012)	(0.014)	(0.013)	(0.016)	(0.016)	(0.016)
N	8850	8850	8850	7928	7928	7928
R^2	0.191	0.190	0.194	0.363	0.364	0.364

Notes: The first three columns ISIC-4digit industry and year fixed effects. The last three columns include firm and year fixed effects. Standard errors are clustered at ISIC-4digit industry. Small size (<20 workers) dummy is the baseline category. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Summary statistics

Country	CUR	Sales	Capital	Labor	Material	Export share	Imp. Penetr	Import share	Elec. outage	Water short	Loan access	No. of competi	Investment	GDP capit
THA	87	13	12	11	11	8	3	1.63	0.07	0.01	0.70	2.29	1.06	9
CHN	85	15	14	13	14	13	2	5.10	0.41	0.04	0.41	4.32	4.73	9
IND	80	13	13	11	13	9	3	6.41	0.63	0.04	0.33	3.68	0.61	7
ZAF	80	14	14	13	13	5	3	14.59	0.46	0.05	0.57	1.50	4.97	9
IDN	79	11	11	10	10	2	2	2.27	0.43	0.04	0.33	1.50	1.31	8
BRA	78	13	16	12	12	3	2	14.08	0.48	0.06	0.13	1.56	6.20	9
HUN	78	15	13	13	14	20	4	22.14	0.26	0.00	0.69	1.53	4.43	9
LKA	76	12	11	10	10	11	3	8.63	0.79	0.14	0.21	2.71	1.30	8
SVN	76	15	15	13	14	38	4	42.20	0.46	0.00	0.32	1.47	10.09	10
SVK	76	16	16	15	14	26	4	34.00	0.32	0.00	0.50	2.09	5.46	10
BGR	75	13	13	11	12	14	4	43.26	0.48	0.07	0.31	2.68	7.35	9
VNM	74	14	13	11	13	25	3	39.62	0.63	0.03	0.41	1.67	7.39	7
SWE	74	16	15	15	15	27	4	45.72	.	.	0.58	1.90	9.16	11
MEX	74	13	13	12	12	4	4	19.89	0.39	0.09	0.18	1.66	2.37	9
HRV	73	14	14	13	13	23	4	42.68	0.37	0.04	0.41	1.57	6.44	9
HND	73	13	12	11	11	9	.	32.40	0.64	0.22	0.49	1.66	4.01	8
EST	73	14	14	13	13	38	4	62.79	0.75	0.07	0.60	1.63	7.18	10
ROU	73	14	13	12	12	14	.	28.68	0.63	0.03	0.24	1.59	4.95	9
ISR	73	15	14	14	14	17	3	36.98	0.17	0.01	0.74	2.93	5.06	10
TTO	72	14	13	12	13	9	4	36.72	0.62	0.13	0.12	1.62	2.49	10
BLR	72	16	14	14	15	22	4	51.46	0.24	0.02	0.44	2.80	4.72	9
RUS	72	14	13	12	13	3	4	35.89	0.30	0.18	0.43	2.70	3.46	9
EGY	72	13	13	11	12	5	4	28.80	0.79	0.08	0.32	4.08	1.11	8
PER	71	14	13	12	13	12	3	38.67	0.40	0.08	0.25	1.64	6.45	9
CHL	71	14	14	12	13	7	4	36.23	0.52	0.02	0.28	1.51	7.23	9
LTU	71	14	13	12	13	34	4	49.26	0.23	0.01	0.41	2.51	2.61	9
ARG	71	14	13	13	13	13	3	24.63	0.66	0.09	0.16	1.55	6.39	10
GRC	70	15	14	13	14	16	4	41.78	0.37	0.03	0.37	2.72	5.64	10
ECU	70	14	13	12	13	5	4	53.10	0.64	0.21	0.31	1.55	6.39	9
GTM	69	13	13	11	12	6	.	39.09	0.60	0.19	0.22	1.63	4.47	8
IRQ	69	12	12	11	11	1	.	23.60	0.72	0.18	0.24	2.88	2.59	8
UZB	69	13	13	11	12	4	.	13.36	0.46	0.02	0.79	2.19	4.54	8
KEN	69	14	13	11	12	21	3	33.91	0.90	0.30	0.20	2.67	3.70	7
NIC	69	12	11	10	10	3	.	34.16	0.76	0.32	0.34	1.53	4.05	7
UKR	69	12	12	11	9	10	4	22.32	0.28	0.13	0.31	2.86	0.06	8
BWA	68	13	13	11	12	9	2	57.60	0.39	0.03	0.32	1.42	5.80	9
COL	68	13	12	12	12	7	4	32.74	0.49	0.07	0.23	1.67	6.18	9
CRC	68	14	13	12	13	12	4	50.07	0.52	0.13	0.10	1.60	4.77	9
SEN	68	12	11	10	10	7	4	29.50	0.96	0.16	0.26	1.56	3.25	7
MKD	68	13	13	11	12	34	4	52.41	0.38	0.20	0.27	1.62	7.14	8
SRB	68	14	14	12	13	14	.	31.10	0.67	0.13	0.22	1.56	7.99	9
PHL	68	14	13	11	13	16	4	26.97	0.44	0.07	0.53	3.46	2.67	8
BDI	67	13	12	11	12	14	2	49.77	0.92	0.21	0.19	2.99	4.41	6
BIH	67	14	14	12	13	28	4	46.97	0.47	0.12	0.28	1.62	6.83	8
COD	66	11	11	9	11	3	.	29.86	0.97	0.14	0.17	1.51	3.45	6
POL	66	14	13	12	13	17	3	24.22	0.19	0.03	0.58	2.58	3.20	9
PRY	66	13	13	11	12	12	4	49.65	0.82	0.18	0.29	1.63	3.18	8
URY	66	14	13	12	13	16	4	58.71	0.37	0.12	0.29	1.60	4.45	10
AFG	66	12	10	10	11	6	7	51.03	0.70	0.08	0.03	2.85	0.46	6
TUN	65	14	14	12	14	29	3	55.33	0.14	0.01	0.49	3.02	5.57	8
MUS	65	13	12	11	11	12	4	41.06	0.44	0.18	0.24	1.38	1.69	9
MNG	65	12	13	11	11	11	4	42.62	0.68	0.20	0.11	1.44	6.23	8
TUR	64	15	14	13	13	30	3	12.23	0.55	0.10	0.69	3.74	2.16	9
LBN	64	14	14	12	13	22	4	52.16	0.98	0.16	0.23	2.71	4.40	9
BFA	63	13	12	10	11	6	.	52.05	0.93	0.06	0.00	1.60	1.96	6
BOL	63	13	12	11	11	12	3	59.52	0.46	0.07	0.22	1.58	3.98	8
MDA	63	13	13	11	12	14	4	34.40	0.25	0.03	0.75	2.91	1.54	8
PAK	63	12	12	10	10	12	3	11.80	0.83	0.09	0.36	3.47	0.45	7
KAZ	62	13	13	12	12	3	5	37.20	0.37	0.10	0.46	2.77	2.28	9
ALB	62	13	13	11	12	19	5	63.43	0.75	0.12	0.40	2.35	1.59	8
DOM	62	14	14	12	13	10	.	55.70	0.75	0.22	0.23	1.55	5.32	9
LVA	61	14	13	12	13	30	4	48.22	0.42	0.07	0.41	2.60	1.69	9
ZMB	61	19	19	17	17	7	3	25.14	0.85	0.24	0.14	3.74	4.70	7
GHA	61	17	17	16	16	11	3	47.74	0.92	0.22	0.11	3.96	1.67	7
JOR	61	14	14	12	13	19	4	42.25	0.15	0.12	0.22	3.91	2.18	8
ETH	59	13	13	10	12	8	4	17.54	0.85	0.35	0.44	3.00	3.76	6
NGA	59	10	10	9	9	14	.	14.06	0.76	0.13	0.24	4.13	1.47	8
YEM	58	11	11	10	10	2	3	33.22	0.91	0.20	0.24	1.62	2.45	8
AGO	58	12	12	10	10	0	5	40.68	0.86	0.30	0.16	1.32	4.19	8
KGZ	58	7	7	4	5	14	5	47.55	0.59	0.12	0.58	2.64	0.00	7
NAM	57	13	13	11	11	6	4	23.30	0.29	0.03	0.11	3.04	1.97	8
MNE	56	13	13	11	12	8	.	53.77	0.62	0.09	0.35	2.26	2.45	9
ARM	56	12	13	10	11	18	5	58.70	0.34	0.12	0.21	1.36	5.40	8
UGA	56	11	11	9	10	8	.	12.62	0.78	0.10	0.10	4.45	1.99	7
MYS	56	12	12	11	11	27	4	14.81	0.30	0.16	0.13	4.27	2.66	9
TZA	55	11	11	10	10	6	4	32.31	0.83	0.18	0.03	3.70	1.77	7
GEO	55	12	12	10	12	9	5	37.47	0.35	0.20	0.32	1.41	3.27	8
AZE	53	13	14	11	12	2	4	8.97	0.24	0.03	0.42	3.59	1.08	9
MAR	49	15	14	12	13	19	3	47.72	0.36	0.01	0.41	2.90	3.64	8
ZWE	49	.	.	.	.	4	4	32.67	0.89	0.26	0.03	2.84	0.00	7
TJK	46	11	12	10	11	8	.	31.79	0.53	0.12	0.39	2.24	2.73	7
NER	45	13	13	10	11	5	5	93.22	0.99	0.22	0.23	3.40	2.92	6

Note: sales, Capital, Labor, Material, Import penetration, Number of competitors, Investment, and GDP per capita are all in log scale.

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