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Is tinkering with institutional quality a panacea for firm performance? Insights from a semiparametric approach to modeling firm performance *

Sumon Kumar Bhaumik†
Sheffield University Management School, University of Sheffield, UK, &
IZA - Institute for Labor Economics, Germany,
Email: s.k.bhaumik@sheffield.ac.uk

Ralitza Dimova
Global Development Institute, University of Manchester, UK, &
IZA - Institute for Labor Economics, Germany
Email: ralitza.dimova@manchester.ac.uk

Subal C. Kumbhakar
Binghamton University, New York, USA
Email: kkar@binghamton.edu

Kai Sun
Email: ksun1@binghamton.edu

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†*Corresponding author*. Sheffield University Management School, University of Sheffield, Sheffield S10 1FL, United Kingdom. *Phone*: +44 114 222 3297. *Email*: s.k.bhaumik@sheffield.ac.uk.

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Abstract

There is a large and growing literature on the impact of institutional quality on economic performance and the broad consensus is that "good" institutions facilitate better economic performance. The literature that provides micro-level support for the policy discourse about institutional quality does not, however, account for significant intra-country variation reactions of firms to changes in business environments, even within the same industry, and it by and large ignores the possibility that the impact of institutional quality on firm performance may not be neutral. In this paper, we analyze the impact of institutions on firm performance using an approach that enables us to overcome these problems with the stylized approach. Using cross-country firm level data, we demonstrate that not only does the marginal impact of institutional quality vary significantly within countries, but also that the impact is economically significant only at the two extremes of the distribution. We view this as *prima facie* evidence that policies that tinker with institutional quality on the basis of the popular wisdom about the impact of these institutions on the *average* firm may not have the desired or expected impact, at least at the micro-level.

Keywords: Institutional quality; Firm performance; Marginal effect; Textiles industry

JEL codes: C14, D24, K31, O43

1 Introduction

There is a large and growing literature on the impact of institutional quality on economic performance and the broad consensus is that "good" institutions facilitate better economic performance (Levine, 1998; Nickell & Layard, 1999; Rodrik *et al*, 2004; Acemoglu & Johnson, 2005; Dollar *et al*, 2005). This literature has spawned popular wisdom about the nature of "good" economic institutions. For example, it is generally accepted that flexibility is a desirable characteristic of labor markets just as intense competition is a desirable characteristic of product markets. Importantly, as "institutional quality" has become part of the lexicon of policymakers around the world, such popular wisdom has the ability to shape (indeed, is already shaping) the nature of policymaking and institution building around the world.

In a literature that has developed in parallel, researchers have examined the impact of various aspects of the business environment on firm performance (Bhaumik & Estrin, 2007; Commander & Svejnar, 2011). The genesis of this literature lies with the argument that if a "good" business environment enhances the productivity of firms, there would eventually be an increase in the overall productivity of industries and entire economies, the pursuit of higher productivity being a key policy objective of governments that seek rapid economic growth. Policy conclusions drawn from this literature are based on point estimates of the impact of the different components of business environment on firm performance. It is argued, for example, that product market competition facilitates productivity growth for the *average* firm. It is similarly argued that "good" institutions facilitate better firm performance, often by way of higher productivity. As such, the firm-level literature that is often based on cross-country studies trying to capture variations in institutional quality (and other aspects of business environment) confirms the popular wisdom about desirable characteristics of institutions.[1]

The literature that provides micro-level support for the policy discourse about institutional quality has two important shortcomings. First, there is often significant intra-country variation in the characteristics of firms, even within the same industry, and their reactions to changes in the business environment are generally not the same. For example, Aghion *et al* (2009) find that the impact of entry of foreign firms on productivity change of incumbent firms in a market depends on their distance from the global productivity frontier. While productivity change is

[1]For a different view about the impact of institutional quality on firm performance, see Bhaumik & Dimova (2014).

mildly positive for (i.e., foreign firm entry has a positive impact on the productivity change of) the average firm, the impact is progressively lower for firms that are further away from the global frontier, and for firms at a greater distance from this frontier the net impact is negative. In other words, where possible, it would be useful to understand the impact of institutional quality (among other things) on *individual firms*, and be mindful about the possibility that this impact would be influenced by firm characteristics and environmental variables.

Second, this literature assumes that factors such as institutional quality have a neutral impact on productivity and hence on output, In fact, the impact of these factors on productivity and output may not be neutral. Put differently, the institutional quality variables affects not only TFP (the intercept term in the Cobb-Douglas production function), but also the productivity of factor inputs such as labor and capital. The stylized regression model captures the direct effect of the institutional factors. There can, however, be an indirect effect. For example, labor institutions are much more likely to affect productivity through improved training and x-efficiency (indirect effect) than through the direct effect. In other words, the empirical relationship between output and inputs should ideally capture the way in which both institutional quality and firm characteristics such as size and quality affect both the efficiency with which factor inputs are used and the direct effect. Expanding on Binswanger (1980) it is possible to argue that introduction of new institutions (and related policies) can alter the share of specific factors of production (most importantly, labor) in the output and income distribution substantially. If so, the nature of the impact of institutional quality on firm-level output – the balance between neutral impact and factor-augmenting impact – should be well understood.[2]

In this paper, we propose an approach that overcomes the methodological approaches in the extant literature. First, we demonstrate that the business environment of an economy, as captured by formal institutions, not only has a neutral impact on productivity, it also affects the contribution of the factor inputs. Perhaps more importantly, for the same industry the impact of formal institutions on productivity of factor inputs vary across countries, with attendant implications for share of factor inputs (in particular, labor) in the value added. Second, we demonstrate that even within a single country formal institutions have different (marginal)

[2]The declining share of labor in output has attracted the attention of economists (Jacobson & Occhino, 2012; Elsby *et al.*, 2013) and the popular press (The Economist, 2013) alike, and promises to one of the most important policy issues/challenges facing governments in the years to come. But much of the emphasis is on impact of technological change rather than on institutional quality, even though changes in labor market institutions is seen as a way to reverse the trend of declining labor's share in output.

impact on firm-level productivity. Taken together, these results demonstrate that a policy prescription based on changes to formal institutions may not have the same impact across and within countries. Some firms are likely to gain much more than others; indeed, for many firms the impact of institutional quality on productivity may be small. At the same time, some countries may experience unintended consequences such as lower share of labor in value added than other countries if institutional quality affect productivity of the factor inputs differently. The policy implications of such inter- and intra-country heterogeneity is significant. We, therefore, provide compelling *prima facie* evidence that the issue of impact of formal institutions on micro- or firm-level performance should be revisited to examine in greater detail the heterogeneous impact of institutional quality on firm performance (specifically, productivity) and better understand the unintended consequences of changes in formal institutions on outcomes such as inequality. This is the main contribution of our paper.

In order to demonstrate the extent of inter- and intra-country variations in the firm-level impact of formal institutions, we focus on a sample of 1625 firms across nine developing countries. The firms belong to the textiles and garments industry in which developing countries arguably have a comparative advantage. We focus on three formal institutions for our analysis, namely, economic freedom which is highly correlated with many of the other formal institutions such as property rights, employment law which has been been the subject of widespread policy debates in developing countries and is often viewed as a key instrument for employment generation, and social security which plays an important role in determining the extent to which laborers are able to preserve their productivity during spells of unemployment and the extent to which they can embrace innovation that is generally bundled with some degree of risk for firms and their employees alike. Our results suggest that, for each measure of institutional quality, i.e., within each country, there is a large dispersion of its marginal impact on firm performance that is not reflected in the average (or mean) impact of these institutional variables on performance. We also find that the marginal impacts of institutional quality on firm performance is small for a vast majority of the firms and that these impacts are economically significant only at the two extremes of the distribution. Finally, the results indicate that the distributions of these marginal effects can vary significantly across countries.

The rest of the paper is structured as follows: The modeling approach is discussed in Section

2. Section 3 discusses the data. The empirical results and the additional insights provided by our approach are discussed in Section 4. Finally, Section 5 concludes.

2 Modeling approach

The stylized literature models (log) output as a linear function of (log) factor inputs, and this function is thereafter extended to include, among other things, measures of institutional and governance quality. Bhaumik and Estrin (2007), for example, model output (or sales) as a function of firm-specific characteristics such as factor inputs and ownership, as well as institutional (and economic) characteristics of the markets in which the firms operate and the regions in which the firms are located. In other words, output of the i^{th} firm is given by

$$Y_i = \theta + X_i^{'}\beta + Z_i^{'}\phi + u_i \tag{1}$$

where Y is (log) output (or sales), X is a k-vector of (log) factor inputs and Z_i is a q-vector of other firm characteristics such as ownership, industry-specific factors such as competition, as well as region or country level institutional features. Finally, u_i is an *iid* noise term. Both industry-specific factors and regional/country-level features are common to a number of firms. Estimates of the ϕ vector capture the impact of factors such as ownership, competition and institutional quality on estimated (log) output (i.e., productivity). Given the inputs, these Z variables can be viewed as productivity shifters and hence their coefficients capture the marginal effects of them on productivity, *ceteris paribus*. The estimated coefficients, however, are exactly the same for all firms.

2.1 Flexible neutral TFP growth model

The specification used in (1) implies that the Z variables affect the productivity of all firms in the exact same way in the sense that their marginal effects are constant. We, however, propose to capture firm-specific impact of the Z variables (which include institutional quality) on productivity, when these variables affect productivity only through TFP. For this, we specify $E(Y_i|X_i, Z_i)$ as

$$E(Y_i|X_i, Z_i) = \theta(Z_i) + X_i^{\prime}\beta \tag{2}$$

where $\theta(\cdot)$ denotes an unknown smooth (i.e., nonparametric) function of the Z variables, and β denotes a k-vector of constant parameters. This specification is popularized by Robinson (1988) and is in line with the TFP model used in Griffith, *et al* (2004), where TFP is defined by $\theta(Z_i)$. In this formulation $\theta(Z_i)$ is a nonparametric function of the Z variables, such that these firm characteristics and (business) environmental factors are allowed to affect TFP growth in a flexible manner in the sense that these effects do not rely on any particular functional form of θ. Furthermore, the effect of one Z variable (say Z_l) on TFP growth will also depend on the level of all the Z variables. This captures non-linearity in the environmental variables (including institutional quality) and TFP growth relationship, as well as their cross-effects, without assuming a specific functional form.

This specification implies that

$$Y_i = E(Y_i|X_i, Z_i) + u_i = \theta(Z_i) + X_i'\beta + u_i \tag{3}$$

where $E(u_i|X_i, Z_i) = 0$. To estimate β, we take the conditional expectation $E(\cdot|Z_i)$ for both sides of (3) and get,

$$E(Y_i|Z_i) = \theta(Z_i) + E(X_i|Z_i)'\beta \tag{4}$$

since $E(u_i|Z_i) = 0$. Subtracting (4) from (3) would yield

$$Y_i^* = X_i^{*'}\beta + u_i \tag{5}$$

where $Y_i^* = Y_i - E(Y_i|Z_i)$ and $X_i^{*'} = (X_i - E(X_i|Z_i))'$. One can view (5) as an ordinary least squares (OLS) regression of Y_i^* on X_i^*. However, before running this regression to estimate β, one would first have to estimate $E(Y_i|Z_i)$ and $E(X_i|Z_i)$. Note that we are not assuming any joint distributions. Thus, to estimate $E(Y_i|Z_i)$ and $E(X_i|Z_i)$ nonparametrically, one could use the Nadaraya-Watson (NW) kernel estimator (see Nadaraya, 1965; Watson, 1964; Li & Racine, 2006). For example, the NW kernel estimator for $E(Y_i|Z_i)$ is

$$\hat{E}(Y_i|Z_i) = \frac{\sum_{i=1}^{n} K(Z_i, z)Y_i}{\sum_{i=1}^{n} K(Z_i, z)}, \tag{6}$$

where n denotes sample size, and

$$K(Z_i, z) = \prod_{l=1}^{q} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{Z_{li} - z_l}{h_l}\right)^2\right) \tag{7}$$

is a product Gaussian kernel function. Finally, h_l is the bandwidth for the l-th Z variable. We choose the bandwidth vector, $h = [h_1, \ldots, h_l, \ldots, h_q]$, using the least-squares cross-validation (Li and Racine, 2006) method. The cross-validation (CV) criterion function is given by

$$CV(h) = \min_{h} \sum_{i=1}^{n} [Y_i - \hat{Y}_{-i}]^2, \tag{8}$$

in which $\hat{Y}_{-i}$ is the leave-one-out NW kernel estimator of $E(Y_i|Z_i)$. This method of selecting the bandwidths is data-driven and allows us to avoid any potential pitfalls associated with an *ad hoc* choice of bandwidths.

The NW kernel estimator for $E(X_i|Z_i)$ can be estimated using the same estimation procedure as used to estimate $E(Y_i|Z_i)$. One can then replace Y_i^* with $\hat{Y}_i^* = Y_i - \hat{E}(Y_i|Z_i)$, and replace X_i^* with $\hat{X}_i^* = X_i - \hat{E}(X_i|Z_i)$ in (5), and the OLS estimator for β is:

$$\hat{\beta} = \left(\sum_{i=1}^{n} \hat{X}_i^* \hat{X}_i^{*\prime}\right)^{-1} \sum_{i=1}^{n} \hat{X}_i^* \hat{Y}_i^* \tag{9}$$

Once $\hat{\beta}$ is estimated, $\hat{\theta}(Z_i)$ can finally be estimated using the relationship given in (4), i.e., $\theta(Z_i) = E(Y_i|Z_i) - E(X_i|Z_i)'\beta$. Replacing the conditional expectations as well as β with their respective consistent estimates gives an estimate of $\theta(Z_i)$, i.e.,

$$\hat{\theta}(Z_i) = \hat{E}(Y_i|Z_i) - \hat{E}(X_i|Z_i)'\hat{\beta}, \tag{10}$$

where $\hat{E}(\cdot|Z_i)$ are the NW kernel estimates. The marginal effects of a particular Z, i.e., z_l, on output is then calculated as

$$\frac{\partial Y_i}{\partial z_l} = \frac{\partial \hat{\theta}(Z_i)}{\partial z_l} = \frac{\partial \hat{E}(Y_i|Z_i)}{\partial z_l} - \frac{\partial \hat{E}(X_i|Z_i)'}{\partial z_l}\hat{\beta}. \tag{11}$$

where

$$\frac{\partial \hat{E}(Y_i|Z_i)}{\partial z_l} = \sum_{i=1}^{n} \frac{\left(\frac{Z_{li}-z_l}{h_l^2}\right) K(\cdot) \sum_{i=1}^{n} K(\cdot) - K(\cdot) \sum_{i=1}^{n} \left[\left(\frac{Z_{li}-z_l}{h_l^2}\right) K(\cdot)\right]}{(\sum_{i=1}^{n} K(\cdot))^2} \cdot Y_i, \tag{12}$$

and $\frac{\partial \hat{E}(X_i|Z_i)}{\partial z_l}$ is computed using the similar method, replacing Y_i in (12) with X_i.

Note that these marginal effects are *observation-specific* so long as the Z_i variables are observation-specific. Thus, both the TFP and the marginal effects of the Z variables on TFP are observation-specific and completely flexible. If one assumes a parametric form of TFP, i.e., $\theta(Z_i)$ is a parametric function of Z_i, the marginal effects will be constant (linear) when $\theta(Z_i)$ is linear (quadratic). That is, although the marginal effects are observation-specific when $\theta(Z_i)$ is quadratic, these marginal effects are linear – not fully flexible. This is important in our application because we want to examine whether marginal effects of institutional quality vary across observations and if so whether there are some patterns that may not be captured in a parametric form of TFP.

2.2 Non-neutral productivity growth model

The previous model allows the Z variables to explain TFP growth in a fully flexible manner but the Z variables affect TFP growth in a neutral fashion (i.e., independent of the X variables). We extend the aforementioned model to allow for indirect effects via the input elasticities which are affected by the Z variables (Li *et al.* (2002) calls this semiparametric smooth coefficient model because it allows the β coefficients to be some unknown smooth functions of Z variables). This extended model therefore enables us to meet the twin objectives of estimating the non-neutral impact of institutional quality on output as well as generate firm-specific estimates of this impact.

In the case of the extended model the conditional expectation is written as

$$\begin{aligned} E(Y_i|X_i, Z_i) &= \theta(Z_i) + X_i'\beta(Z_i) \\ &= W_i'\gamma(Z_i) \end{aligned} \tag{13}$$

where both $\theta(\cdot)$ and $\beta(\cdot)$ denote unknown smooth functions of the Z variables, $W_i' = [1 \; X_i']$, $\gamma'(Z_i) = [\theta(Z_i) \; \beta'(Z_i)]$, both W_i and $\gamma(Z_i)$ are of dimension $(k+1) \times 1$. This specification implies that

$$Y_i = W_i' \gamma(Z_i) + u_i \tag{14}$$

Pre-multiplying (14) by W_i and taking the conditional expectation $E(\cdot|Z_i)$ would yield

$$E(W_i Y_i | Z_i) = E(W_i W_i' | Z_i) \gamma(Z_i) \tag{15}$$

since $E(W_i u_i | Z_i) = 0$. Rearranging (15) we get

$$\gamma(Z_i) = [E(W_i W_i' | Z_i)]^{-1} E(W_i Y_i | Z_i) \tag{16}$$

Following Li & Racine (2006), one would then be able to employ the kernel method to estimate $\gamma(Z_i)$ as

$$\hat{\gamma}(z) = \left[\sum_{i=1}^{n} W_i W_i' K(Z_i, z) \right]^{-1} \sum_{i=1}^{n} W_i Y_i K(Z_i, z) \tag{17}$$

where $K(\cdot)$ is the product Gaussian kernel function as defined in (7). The bandwidth vector, h, is selected via the least-squares cross-validation method (Li & Racine, 2010) by the criterion

$$CV(h) = \min_h \sum_{i=1}^{n} [Y_i - W_i' \hat{\gamma}_{-i}(Z_i)]^2 M(Z_i), \tag{18}$$

where $W_i' \hat{\gamma}_{-i}(Z_i) = W_i' \left[\sum_{j \neq i}^{n} W_j W_j' K(Z_j, z_i) \right]^{-1} \sum_{j \neq i}^{n} W_j Y_j K(Z_j, z_i)$ is the leave-one-out kernel conditional mean, and $0 \leq M(\cdot) \leq 1$ is a weight function that serves to avoid difficulties caused by dividing by zero.

Finally, the marginal effects of a particular Z, i.e., z_l, on output is calculated as

$$\frac{\partial Y_i}{\partial z_l} = W_i' \frac{\partial \hat{\gamma}(Z_i)}{\partial z_l} = \frac{\partial \hat{\theta}(Z_i)}{\partial z_l} + X_i' \frac{\partial \hat{\beta}(Z_i)}{\partial z_l}. \tag{19}$$

See Kumbhakar & Sun (2012) for the formula of $\frac{\partial \hat{\gamma}(Z_i)}{\partial z_l}$. The marginal effects in the model in Section 2.1 are observation-specific provided that the Z_i variables are observation-specific. The present non-neutral model is more flexible in the sense that even if the Z variables are not observation-specific, the marginal effects will be obseravtion-specific and will depend on the X_i variables. In the present model the overall marginal effects of the z_l variable on the output variable is decomposed into a direct (neutral) component ($\frac{\partial \hat{\theta}(Z_i)}{\partial z_l}$) and a non-neutral component working through the $\beta(.)$ coefficients $(X_i' \frac{\partial \hat{\beta}(Z_i)}{\partial z_l})$. Thus, for example institutional quality can affect output directly as well as indirectly through the β parameters.

3 Data

In order to examine the impact of institutional quality on firm performance, we bring together data from three different sources. The firm-level data on measures of output and input, size and ownership are obtained from the World Bank Enterprise Surveys which collect data from manufacturing sector firms from around the world. The surveys use standardized survey instruments, making data from different countries comparable, and have been used in a number of firm-level research in developing economy contexts (e.g., Amin, 2007, 2009; Eiferf *et al*, 2008; Bhaumik & Dimova, 2013, 2014). We pool together cross-section data sets from countries that were surveyed between 2002 and 2005. Nominal variables used for the estimation of the production function were converted into real US dollars, thereby making them comparable across the countries.[3] As such, our base production function involves the use of the dollar value of output as the dependent variable, and (log) labor, (log) capital and (log) materials as the independent variables. In the literature, this is an acceptable variation of the use of (log) value added as the dependent variables, and (log) labor and (log) capital as the independent variables. World Bank Enterprise Survey data have been used to estimate similar production functions; see Bhaumik & Dimova (2013, 2014).

The firm level data set also gives us our measure of firm size which is a categorical variable that ranks firms on a 5-point scale. The categories themselves are based on the number of employees.[4] It also gives us our control for ownership. We have continuous data for proportion of a firm that is owned by the state, domestic private investors and foreign investors. However, with a few exceptions, the largest shareholder of each firm - whether the state, domestic private or foreign - owns close to 100 percent of the shares. Hence, instead of using the continuous

[3]The cross-section nature of the data does not permit the use the permanent inventory method to estimate firm-level capital stock. However, this weakness of survey data, especially for developing countries, is widely recognized in the literature, and the non-use of the permanent inventory method is tolerated (e.g., Bhaumik & Estrin, 2007).

[4]In stylized regression models such as OLS it is customary to deconstruct categorical variables into a series of dummy variables and use these dummy variables in the regression model. However, note that we are modeling a production function that already has (log) labor and (log) capital as explanatory variables, such that the categorical measure of firm size gives us a firm's position within the size distribution, and it is a component of Z. We, therefore, use this categorical variable as a continuous variable for our estimations.

variables, we use dummy variables to indicate the type of the controlling owner. Since fewer than 2 percent of domestic firms are state owned, it is meaningless to distinguish between state-owned and privately-owned firms. We, therefore, control for foreign ownership alone. In our sample, 4.5 percent of the firms are foreign owned.

We merge this firm level data with country level measures of institutional quality from two different sources. As mentioned earlier in the paper, for the purpose of our paper, we focus on three measures of formal institutions. These are as below:

Economic freedom. It is stylized in the economics literature that a private economic agent's ability to engage in production efficiently depends on a variety of factors such as property rights, rule of law, (lack of) pre-emption by governments through fiscal imbalance, ability to trade freely with other economic agents etc. These sub-components of economic freedom are, unsurprisingly, highly correlated with each other, and hence an overall measure of economic freedom that encompasses a wide range of formal institutions ranging from property rights to trade freedom is as good as any. As such, economic freedom both provides firms an incentive to innovate and use resources efficiently by increasingly contestability of the market[5] and, at the same time, enables them to achieve these objectives by providing greater freedom with respect to implementation of their strategic choices. In particular, we use the index of economic freedom provided by the Heritage Foundation, which has emerged as a major source of measures of institutional quality (see Johnson *et al*, 1998; Klapper *et al*, 2004).[6] The index ranges in value from 0 to 100, with institutional quality or quality of business environment increasing in the value of the index. The index is correlated with other measures of institutional quality such as the Corruption Perception Index published by the Transparency International.

Employment law. There is widespread discussion in the literature about the correlation (even causal relationship) between labor market flexibility and outcomes such as new firm entry and employment rates (Nickell, 1997; Besley & Burgess, 2004), but the relationship between employment law and productivity is less well explored. However, it is easy to make the case that labor market flexibility, as influenced by employment law, can (and indeed will) affect

[5]For a discussion about the importance of institutional quality for firm entry and market contestability, see Bhaumik *et al.* (2009).

[6]The alternative is to use the first principal component of all the sub-indices of the economic freedom index. However, principal components are difficult to interpret from an economic standpoint and there is no compelling reason to believe that this mathematical construct would be a better proxy for the economic environment in a country than the economic freedom index itself.

productivity. On the one hand, it can be argued that greater labor market flexibility leads to more efficient use of labor and also perhaps to better match between skills and opportunities. On the other hand, it has been argued in related literature that lower flexibility with respect to hiring and firing may actually result in greater investment in training and on-the-job learning (Storm & Naastepad, 2007), and greater employee commitment (Michie & Sheehan, 1999). Further, the efficiency wage literature suggests that where labor contracts are incomplete, worker efforts are correlated to their wages (Fehr & Falk, 1999), such that a weakened link between wages and prevailing (un)employment rate may be better from the standpoint of productivity. In other words, greater "rigidity" of labor markets may actually contribute to higher labor productivity (Arunampalam & Booth, 1998). If labor market rigidity also induces employers to invest in research and development and new technology (Michie & Sheehan, 1999), there would also be an impact on TFP. We use an index of employment protection proposed by Botero *et al.* (2004) that captures the degree of labor market flexibility, with a larger index value indicating greater restrictions or, conversely, lesser flexibility.[7]

Social security. It is well understood in the literature that insurance that protects individuals against loss of income in the present (e.g., through unemployment benefits) as well as in the future (e.g., through social pensions) foster income- (and hence productivity-enhancing risk-taking (Sinn, 1996). A corollary of this proposition is that workers who are protected against current and future income shocks (at least to some extent) would be more open to firm-level innovation. This is especially true in contexts such as developing economies (and increasingly in developed economies) where frictions in the capital market make it difficult to smooth consumption over employment cycles. We also know that access to non-wage income during spells of unemployment or adverse health shocks enables workers to preserve their ability to be productive, by way of sustaining productivity-inducing levels of nutrition (Dasgupta & Ray, 1986). On the other hand, like any other insurance, social security and social insurance can induce moral hazard that is generally discussed in the context of labor supply and time spent out of work (Krueger & Meyer, 2002), but which also has implications for a worker's incentives to increase productivity. In this paper, we use an index proposed by Botero *et al.* (2004) that

[7]The choice of indices that propose to capture quality and/or strength institutions, regulations etc are always controversial; each index or measure has its own strengths and weaknesses. We choose the measure proposed by Botero *et al.* (2004) because it measures labor market rigidity, and is widely used and cited, as reflected in more than 1800 citations on Google Scholar. We view it as being adequate for the purpose of our paper.

captures the extent of protection provided to employees against old age, death and disability, sickness and health care coverage, and unemployment benefits, i.e., the degree of protection provided by social safety nets. The value of the index increases with the extent of protection.

Our data are limited in part because of missing information in the World Bank Enterprise Survey data, and in part because the Botero *et al* (2004) paper does not provide measures of labor market institutions for all countries. An outcome of this limitation is that for most individual industries we either have relatively small samples, or little cross-sectional variation with respect to countries. Since the focus of our analysis is the impact of institutional quality on firm performance, and given that measures of institutional quality are only available at the country level, our sample has to be spread across a fair number of countries. At the same time, it is stylized in the literature to estimate production functions separately for individual industries, based on the reasonable assumption that the marginal impact of factor inputs on output vary across industries, such that we require a reasonably large sample for each industry that is analyzed. Only one industry, viz, textiles and garments, meets both these criteria. It gives us a cross-section of 1625 firms, spread across nine developing countries: Brazil, China, Egypt, India, Indonesia, Malawi, Pakistan, South Africa and Zambia.

The textiles and garments industry however has characteristics that are quite suitable for our analysis. To begin with, it is an industry in which developing countries have comparative advantage. Recent estimates suggest that the ratio of the share of textiles and garments in exports of individual developing countries to the ratio of textiles and garments in world exports is significantly greater than one for many developing countries, indicating that developing countries have a comparative advantage in these products (Nordås, 2004).

At the same time, the nine countries in our sample also have quite different levels of institutional quality (Table 1). Consider, for example, economic freedom, which is our measure of the quality of the business environment. At one extreme we have a country like South Africa with an index of economic freedom that is 67.1, very close to the threshold of 70 for "mostly free" countries, and at the other end we have India with an index value of 51.2, just above the threshold of 50 below which lie the "repressed" countries. The indices capturing the quality (or nature) of labor market institutions too vary significantly across the countries. At the one extreme, we have countries such as South Africa (1.04) that have quite flexible employment laws,

Table 1: Measures of institutional quality

Country	Employment law	Social security	Economic freedom
Brazil	2.40	1.65	63.4
China	1.62	2.24	52.6
Egypt	1.62	2.22	55.5
India	1.30	1.20	51.2
Indonesia	1.75	0.53	55.8
Malawi	1.72	0	54.7
Pakistan	1.17	1.39	55.8
South Africa	1.04	1.69	67.1
Zambia	1.15	0.32	59.6

The indices for employment law and social security are taken from Botero *et al.* (2004), and the index for economic freedom is taken from Heritage Foundation. The data indicates that even for our limited sample of nine countries there is a fair amount of variation in institutional quality.

and at the other extreme we have countries such as Brazil (2.40) where there is a fair degree of rigidity. Similarly, in countries like Malawi (0) and Zambia (0.32) there is very little (or no) protection for laborers in the form of social safety nets, and, at the other extreme, countries like China (2.24) and Egypt (2.22) provide a fair degree of protection.

In other words, even though difficulties with the data require us to focus on one industry, the chosen industry is one in which developing countries have comparative advantage, such that it is important for export growth (and consequently employment generation) in these countries. It is sufficiently large to provide significant variations across firms with respect to characteristics such as size and ownership. It also includes data from nine countries that are significantly different with respect to the quality (or nature) of their institutions. In other words, there is a fair degree of variation in the values of the Z variables among the firms in our sample.

4 Insights from regression results

To recapitulate, we estimate *observation-specific* (or *firm-specific*) impact of institutional quality on (log) output. We first estimate this firm-specific impact in a model in which institutional quality affects (log) output neutrally, only through TFP. We then estimate firm-specific impact in a model in institutional quality affects (log) output both through TFP and through the efficiency with which the firm uses factor inputs such as labor and capital. This ability to estimate the impact of institutional quality for individual firms enable us to discuss within-country variations in the firm-level impact of institutional quality on firm performance, which is the basis for some of our key insights. In the rest of this section we discuss our empirical findings and their implications for the discussion (or debate) about the micro-level impact of institutional quality.

To begin with, we report the estimates of the Robinson's model, in which institutional variables have a neutral impact on TFP growth. In this model, (log) output is a linear function of (log) factor inputs, as in a stylized OLS specification, but where the intercept term, θ, is a flexible function of the aforementioned Z variables. Thus, in this model the Z variables affect productivity neutrally which is modeled by the nonparametric function $\theta(.)$ The coefficient estimates for the (log) labor, (log) capital and (log) materials variables are 0.3727, 0.3807 and 0.1962, respectively, and all of them are significant at the 5 percent level. These estimated coefficients are input elasticities, the sum of which gives us an estimated returns to scale of 0.9496, which is consistent with the stylized argument that mature industries exhibit constant returns to scale. While our results, which involve estimates of distributions of marginal impact of institutional quality on $\theta(.)$ and the β parameters, are not directly comparable with the point estimates of impact of institutional quality on output (or value added) in the stylized literature, this estimate of returns to scale for the Robinson's model, which is closest to the stylized specification in our empirical set up, gives us confidence about our empirical estimates.

Next, in Table 2, we report the firm-specific values of the intercept term, θ, and the estimated firm-specific marginal impact of three measures of institutional quality (which are included in the Z vector).[8] Following the literature, the intercept term in a (log) linear model, θ, can be interpreted as TFP growth and the aforementioned marginal impact (or effects), $\partial\theta/\partial Z_i$ are therefore the direct effect of the Z variables on TFP change. Specifically, we focus on the marginal impact of the Botero *et al.* (2004) indices for employment law (Z_1) and social security (Z_2), and the Heritage Foundation index for economic freedom (Z_3). The estimates, reported in Table 2, suggest the following:[9]

[8]The values within parentheses are the bootstrapped standard errors for the firm-specific estimates.

[9]Note that each column in the table reports the distribution for a single estimate, whether θ or $\partial\theta/\partial Z_k$, and hence the table should be read vertically, along the columns. The numbers do not indicate, for example, that the maximum value for $\partial\theta/\partial Z_1$ and that for $\partial\theta/\partial Z_2$ occurs for the same firm.

Table 2: Regression estimates: Neutral impact of institutional quality on TFP and output

Point on the distribution	θ	$\partial\theta/\partial Z_1$	$\partial\theta/\partial Z_2$	$\partial\theta/\partial Z_3$
Mean	1.5633	0.0459	-0.0079	-0.0118
	(0.0467)	(0.0075)	(0.0022)	(0.0014)
1st percentile	0.8662	-0.6101	-0.2698	-0.2110
	(0.1472)	(0.0107)	(0.0277)	(0.0748)
10th percentile	1.1801	-0.0687	-0.0213	-0.0290
	(0.0521)	(0.0030)	(0.0007)	(0.0028)
25th percentile	1.2811	0.0000	-0.0040	-0.0138
	(0.0059)	(0.0041)	(0.0001)	(0.0000)
50th percentile	1.3629	0.0000	0.0000	0.0000
	(0.0007)	(0.0000)	(0.0000)	(0.0000)
75th percentile	1.6037	0.0583	0.0006	0.0001
	(0.3461)	(0.0028)	(0.0002)	(0.0001)
90th percentile	2.5831	0.1548	0.0028	0.0014
	(0.0485)	(0.0055)	(0.0005)	(0.0005)
99th percentile	3.7703	1.2470	0.0937	0.1104
	(0.0643)	(0.4711)	(0.0051)	(0.0048)

The regression estimates indicate that there was a considerable degree of variation in the neutral impact of institutional quality on TFP and output. However, the marginal impact of Z_i on θ are economically significant only at the two tails of the respective distributions.

1. The estimated value of θ (or the intercept) is positive for the entire distribution of θ, which is consistent with stylized estimates of log linear production functions.

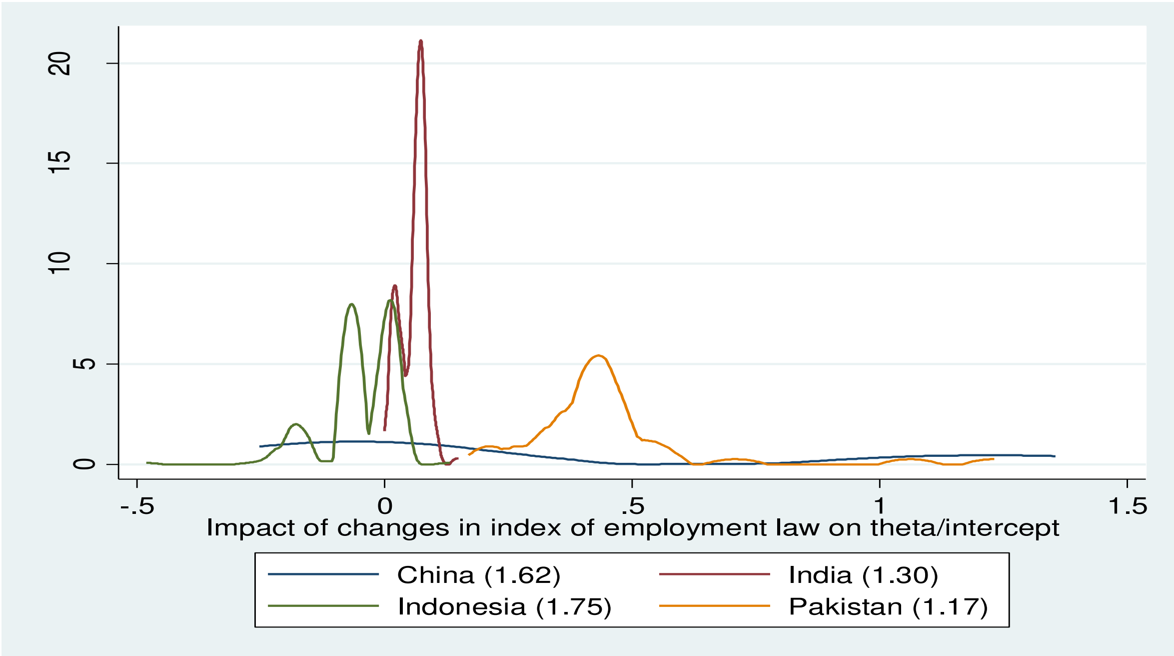
2. For each measure of institutional quality, there is a large dispersion of its marginal impact on firm performance that is not accurately reflected in the *average* (or mean) impact of these institutional variables on performance.

3. More importantly, the marginal impacts of the measures of institutional quality are very small (and hence negligible from the economic point of view) for the vast majority of the firms; they are economically significant only at the two ends of the distribution.[10]

Our results provides a glimpse of a possibility that while institutional quality may have relatively small marginal effects on the performance of only a minority of firms, there could be significant winners and losers of changes in institutional quality, something that stylized

[10]For example, the distribution of the marginal impact of the index of employment law has very small values between the 25^{th} and 75^{th} percentiles.

Figure 1: Firm-level variation in impact of changes in employment law: Within- and between-country variation



empirical approaches do not (or cannot) adequately demonstrate.[11] There is, therefore, *prima facie* evidence that policies that tinker with institutional quality on the basis of popular wisdom about the impact of these institutions on the *average* firm may not have the desired or expected impact. This is easily demonstrated by examining within-country and between-country differences in the distribution of firm-level impact of changes in institutional environment, and we highlight this in Figure 1. In this figure, we report the distributions of $\partial\theta/\partial Z_1$, i.e., the impact of (the index of) employment law on firm performance through an impact on TFP, for four Asian exporters of textiles products. Recall that the Botero *et al.* (2004) index for employment law is constructed such that higher values indicate greater employment protection. We, therefore, have a fair degree of variation ranging from low employment protection in Pakistan (1.17) to a fair degree of protection in Indonesia (1.75).

[11]Our methodology also allows us to have a sense of which of the estimated firm-specific marginal effects are statistically significant. Following Zhang *et al.* (2012) and Henderson, Kumbhakar & Parmeter (2012), we can generate confidence intervals for the firm-specific marginal effects of the k^{th} institutional variable Z_k. We first plot $\partial\hat{\theta}/\partial Z_k$ against $\partial\hat{\theta}/\partial Z_k$, which plots $\partial\hat{\theta}/\partial Z_k$ along the 45 degree line. Thereafter, we can generate the upper and lower confidence bounds by adding and subtracting, respectively, twice the standard error from $\partial\hat{\theta}/\partial Z_k$. This gives us an observation-specific confidence interval for each marginal effect on the 45 degree line. See, for example, Figure 4 in Bhaumik, Kumbhakar & Sun (2014). However, for the purposes of this paper, we abstract from a discussion about statistical significance.

The country-level distributions reported in Figure 1 indicate that, to begin with, there are significant country level differences in the impact of employment law on productivity. For example, firm-level impact of employment law can be quite significant in Pakistan but the impact is negligible in India and for a large proportion of firms in Indonesia. In other words, if productivity enhancement in the textiles sector is an important objective of the Indian policymakers, they are likely to find it difficult to achieve it by altering the flexibility/rigidity of the employment law, *given the size, age and ownership of the firms and the other components of the aforementioned Z vector.* It is also evident from the figure that there are significant within-country variations, and the extent of these within-country variations differ significantly across countries. The range of firm-level impact of employment law is small in India, somewhat larger in Indonesia and Pakistan, and very large in China. There are also interesting differences between the Indonesian and Pakistani distributions, despite their similar ranges of impact. The Indonesian distribution has a long lower tail and a short upper tail, and is (roughly) bimodal. The Pakistani distribution, by contrast, is single-peaked with a short lower tail and a long upper tail. If patterns exist in the within-country impact of employment law (and other institutional variables), for example, if the impact is greater on firms of certain size or certain ownership, it is easy to see how availability of firm-specific estimates of this impact would enable us to easily isolate and identify these patterns.

Next, we report the estimates of the SPSC model in which institutional quality affects productivity in a non-neutral manner, i.e., they have both a direct impact via θ, and also an indirect effect through their impact on the efficiency with which the factor inputs are used in the production process. Formally, given our flexible production function, the marginal impact of the k^th institutional variable Z_k on (log) output, y, is given by

$$\frac{\partial y}{\partial Z_k} = \frac{\partial \theta}{\partial Z_k} + \frac{\partial \beta_1}{\partial Z_k} l + \frac{\partial \beta_2}{\partial Z_k} k + \frac{\partial \beta_3}{\partial Z_k} m \tag{20}$$

where l is (log) labor, k is (log) capital and m is (log) materials.[12] We shall focus on the impact of institutional quality on the efficiency of use/productivity of factor inputs which, as we noted earlier, has implications for share of factor inputs in the output and on income distribution. Further, to maintain consistency with the earlier analysis, we shall focus on the impact of (the

[12]In the Robinson model $\partial y / \partial Z_k = \partial \theta / \partial Z_k$ and hence does not have to be computed separately.

index of) employment law on the productivity of labor and capital.

Table 3: Regression estimates: Coefficients and returns to scale

Point on the distribution	β_1	β_2	β_3	Returns to scale
Mean	0.3958	0.3872	0.2062	0.9892
	(0.0120)	(0.0119)	(0.0067)	(0.0278)
1st percentile	0.1170	-0.0303	-0.1577	0.7891
	(0.0264)	(0.0044)	(0.0138)	(0.0180)
10th percentile	0.1850	0.1117	0.0815	0.8674
	(0.0005)	(0.0003)	(0.0032)	(0.0014)
25th percentile	0.2883	0.3204	0.1476	0.9441
	(0.0009)	(0.0014)	(0.0004)	(0.0013)
50th percentile	0.3925	0.3965	0.2161	1.0052
	(0.0092)	(0.0071)	(0.0050)	(0.0037)
75th percentile	0.4792	0.4382	0.2355	1.0216
	(0.0556)	(0.1420)	(0.0227)	(0.2509)
90th percentile	0.5940	0.5933	0.3482	1.0625
	(0.0074)	(0.0066)	(0.0020)	(0.0061)
99th percentile	0.8519	0.8460	0.4237	1.2447
	(0.0305)	(0.0250)	(0.0079)	(0.0087)

This table reports the impact of institutional change on the efficiency with which factor inputs – (log) labor (β_1), (log) capital (β_2), (log) materials (β_3) – are used in the production process. The estimates reported in the table suggests that (a) there is considerable variation in the impact of Z_i on efficiency of factor inputs across firms, and (b) a high value of the impact of Z_i on the efficiency of one factor input is not necessarily offset by a low value of impact on the efficiency of some other factor input.

Estimated coefficients of the SPSC model are reported in Table 3; β_1 is the coefficient of (log) labor, β_2 is the coefficient of (log) capital, and β_3 is the coefficient of (log) materials.[13][14] Recall that in the SPSC model we generate firm-specific estimates of the βs and therefore also a firm-specific estimate of returns to scale.[15] The numbers reported in the table suggest that there are significant variations in the extent to which the factor inputs contribute to output, and that the difference is particularly high between the upper (around the maximum value) and

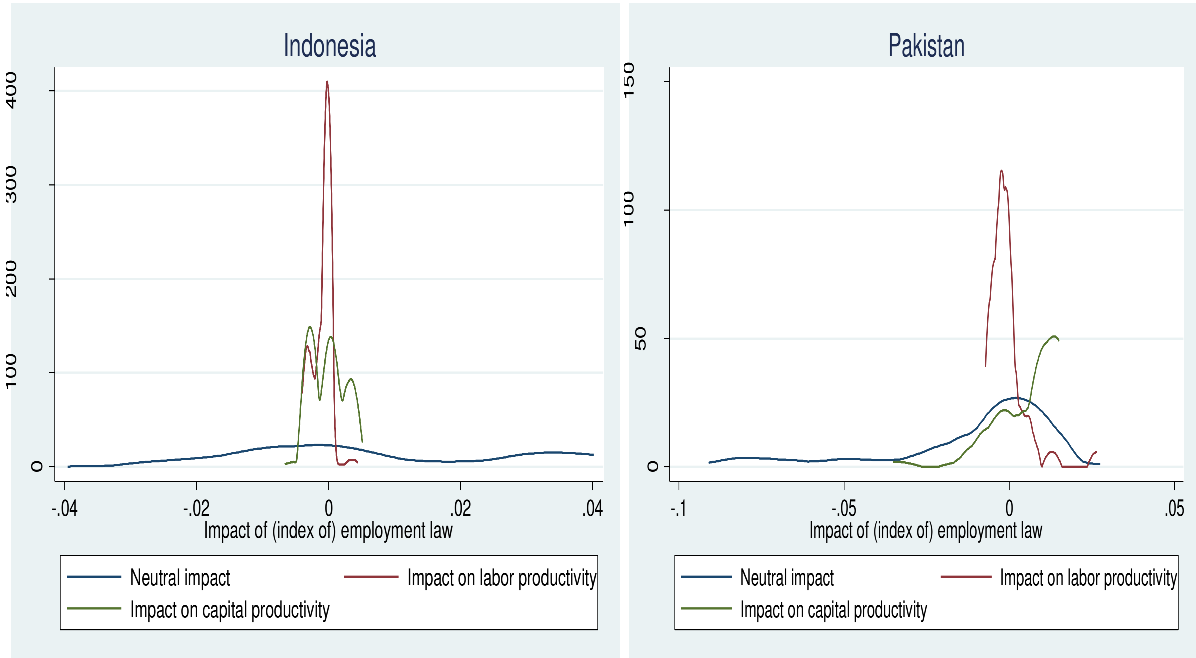
[13]Note that when appropriate constraints are not imposed on the coefficients of the (log) factor inputs, the firm-specific estimates may have negative values which are not meaningful from an economic perspective. However, our unconstrained estimates suggest that the requirement for non-negative coefficients of (log) factor inputs was violated in only 0.53 percent cases for (log) labor, 6.86 percent cases for (log) capital and 2.44 percent cases for (log) materials. Hence, we have reported the unconstrained estimates of the SPSC model. The methodology for imposing suitable constraints on the non-neutral TFP growth model is outlined in Appendix A.

[14]Following Zhang *et al.* (2012) and Henderson *et al.* (2012), we can also generate confidence intervals for the firm-specific βs and the marginal effects of the Z variables on the βs and (log) output. We find the vast majority of the firm-specific estimates of the βs to be statistically significant and hence do not report them for the sake of parsimony. They can be obtained from the authors upon request.

[15]As before, the table should be read along the columns.

lower (around the minimum value) tails. Interestingly, the distribution of the returns to scale estimates indicate that a high estimate of one of the βs is not always offset by lower values of the other βs. For some firms the returns to scale are considerably higher than or lower than one.

Figure 2: Marginal impact of (index of) employment law on TFP and factor inputs: Within- and between- country variation



In Figure 2 we report the marginal impact of employment law on TFP (i.e., the intercept term) and the factor inputs, for Indonesia and Pakistan. Figure 2 indicates the following:

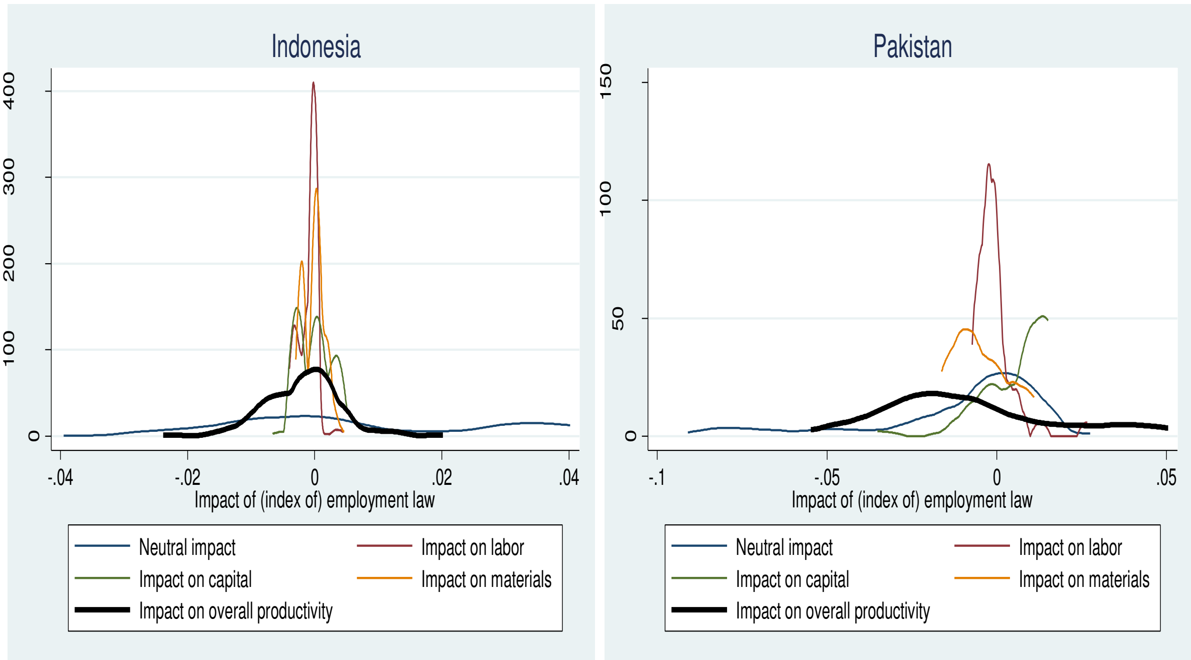
1. The marginal impact of employment law on the contribution of labor to output is low, with a mean of about zero and very little variation around the mean.

2. There is much greater variation in the marginal impact of employment law on the contribution of capital to output, and the marginal impact on capital is much greater in Pakistan (mean = 0.006) than in Indonesia (mean $\approx$ 0).

3. There is much greater variation in the marginal impact of employment law on TFP growth as well, and this impact is much greater in Indonesia (mean = 0.007) than in Pakistan (mean = -0.012)

In other words, changes in the employment law may not have the desired impact on the contribution of labor to output. At the same time, it is much more likely to have an impact on the share of factor inputs in Pakistan than in Indonesia, and may favor owners of capital in a context where policies and institutional changes that fail to augment labor's share in output might adversely affect income distribution in the longer run.

Figure 3: Marginal impact of (index of) employment law on productivity: Within- and between-country variation



Recall that from the marginal impact of institutional quality (and other Z variables) on θ (i.e., TFP) and the βs (i.e., efficiency of use of factor inputs), we can generate the marginal impact of institutional quality on overall (log) output, using equation (20). We therefore add to Figure 2 the marginal impact of (index of) employment law on (log) output, and report it in Figure 3. The figure indicates that there is significant variation in the marginal impact of any institutional quality on (log) output: the range of values for the marginal effect of employment law is 4 percent in Indonesia and 10 percent in Pakistan. Our estimates suggest that the range also varies considerably across countries, even when the estimates for countries such as Malawi and Zambia that have small samples are ignored. The range for other countries are as follows: negligible for Brazil and South Africa, 1.6 percent for China, 21 percent for Egypt, and 7 percent for India. In other words, tinkering with the quality of any institution on the basis of the estimated impact on the *average* firm, from the stylized literature, can give rise to winners and losers and, as we have noted earlier, that outcome would be influenced by other institutions that affect firm performance and also firm characteristics such as age, size and ownership.

The regression estimates reported in this section indicate that institutional quality does not have the same impact on TFP at the firm- (or micro-) level across countries and even within countries. Institutions that characterize the environment in which firms operate interact with each other and also with other factors such as age, size and ownership of firms – both θ and the βs are functions of Z that include all these firm characteristics as well as the environmental factors – giving rise to potentially significant variation in both within- and between- country firm level impact of institutions. Pursuing policies that alter institutional quality on the basis of point estimates of the impact of an institution on firm performance, which capture the impact on the *average* firm can, therefore, give rise to winners and losers, and the outcome would depend on the other institutions that characterize the environment and firm characteristics. Further, institutions do not necessarily have a direct impact on productivity through TFP; they also affect the extent to which factor inputs like labor and capital contribute to output and thereby affect productivity indirectly. Our estimates suggest that the relative magnitudes of the direct (or neutral) impact and the indirect (or non-neutral) impact can differ significantly across countries, and within the same country the impact on labor and capital (and other factor inputs) can differ significantly. Institutional quality can therefore have context-specific impact on the share of factor inputs in the output and hence on income distribution. Importantly, none of these issues come to light when stylized regression specifications are used to model the impact of institutional quality (and other environmental variables) on productivity, and therein lies the advantages of the proposed flexible approach. Unsurprisingly, specification tests described in the Appendix B reject the OLS specification in favor of the neutral and non-neutral flexible specifications at the 1 percent level.

5 Conclusion

With the increasing recognition of the central role of institutions in driving economic outcomes, policymaking is increasingly about designing institutions that would spur private sector growth, especially in the developing countries. Academic research that informs this policy making process is largely based on cross- country analysis of the impact of institutions on economic performance, generally at the macro level, but increasingly also at the micro level. Given the nature of stylized econometric analysis, the policy making process is based on the point estimate of the impact of institutions on the performance of the *average* unit of analysis. By its very nature, therefore, stylized analysis does not fully acknowledge the differential impact of institutions on performance of winners and losers, often prescribing an one-size-fits-all set of institutions. Further, when the unit of analysis is firms (or industries), stylized analysis implicitly assumes that the impact of institutions (and variables characterizing the business environment, in general) affect productivity neutrally, only through the TFP. Hence, the stylized analysis does not recognize the differential impact of institutions on factor inputs, which has implications for, for example, labor's share in the output and, by extension, income distribution.

In this paper, we estimate the impact of institutional quality on firm performance in developing countries using an approach that addresses the methodological weaknesses of the stylized literature. Our estimates indicate that there are large intra- and inter-country differences in the firm-level impact of institutions on firm performance, as measured by productivity. Further, the relative impact on TFP and factor inputs differ across countries, implying that imposition of the same (in this case, labor market) institution in different countries can have very different impact on labor's share of output and hence on income distribution.

Our results provide strong *prima facie* evidence that the issue of the impact of institutions on economic performance should be revisited. In particular, attention should be paid to the differences in the impact of institutions on economic agents such as firms, and on the potential unintended consequences of setting institutional structures and standards on second order outcomes such as labor's share of output and income distribution.

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A Constrained non-neutral TFP growth model

While the semiparametric specification of Li *et al* (2002) is more flexible, the price one has to pay for the flexibility is the higher probability of empirical violations of economic conditions. In estimating a flexible model, one cannot guarantee positive estimates of input elasticities for each observation. Negative input elasticity implies negative marginal products, which is counter-intuitive. To overcome this shortcoming, we propose a constrained semiparametric smooth coefficient model, where we are able to guarantee that all the input elasticity estimates are non-negative. To do this, we rewrite (17) as

$$\hat{\gamma}(z) = \sum_{i=1}^{n} A_i(W_i, Z_i, z)Y_i \tag{21}$$

where $A_i(\cdot) = \left[\sum_i W_i W_i' K_h(Z_i, z)\right]^{-1} W_i K_h(Z_i, z)$. The idea of imposing the observation-specific constraints is simply re-weighting each observation of the dependent variable, Y_i. To do this, we rewrite (21) as

$$\hat{\gamma}(z) = n \cdot \sum_{i=1}^{n} A_i(W_i, Z_i, z) \cdot p_u \cdot Y_i \tag{22}$$

where $p_u = n^{-1}$ denotes the uniform weights. The unconstrained semiparametric smooth coefficient estimator is given in (22). To impose the constraints, we can write the constrained estimator as

$$\hat{\gamma}^*(z) = n \cdot \sum_{i=1}^{n} A_i(W_i, Z_i, z) \cdot p_i \cdot Y_i \tag{23}$$

where $\hat{\gamma}^*(z)$ denotes the constrained smooth coefficient estimator, p_i denotes the observation-specific weights, and $\sum_i p_i = 1$. To select optimal p_i, we follow the Racine *et al* (2011) approach and minimize the L_2 norm criterion function:

$$\begin{gathered}\sum_i (p_i - p_u)^2 \\ \text{subject to } \hat{\beta}(z) \geq 0\end{gathered} \tag{24}$$

This is a quadratic programming procedure and the *quadprog* package in *R* to solve for optimal p_i.[16]

[16]R codes for imposing these constraints are available from the authors upon request.

B Specification test

We are able to test whether the semiparametric models proposed in the earlier sections are necessary, or whether ordinary least squares (OLS) is sufficient to estimate the augmented production function.

B.1 Robinson's partially linear versus OLS estimator

In this section, we describe the procedure of testing Robinson's partially linear versus OLS estimator. Explicitly, we would like to test the null hypothesis $H_0 : \theta(Z_i) = \theta_0 + Z_i'\theta_1$ in (3). The linear neutral TFP growth model is preferred if the null cannot be rejected. To perform the test, we follow Robinson (1988) to construct the Hausman (1978)-type specification test statistic:

$$\hat{T}_n = n\hat{\sigma}^{-2}(\hat{\beta} - \tilde{\beta})' \left\{ S_{X^*}^{-1} - n \left[\sum_i X_i X_i' - \sum_i X_i \tilde{Z}_i' \left(\sum_i \tilde{Z}_i \tilde{Z}_i' \right)^{-1} \sum_i \tilde{Z}_i X_i' \right]^{-1} \right\}^{-1} (\hat{\beta} - \tilde{\beta}) \tag{25}$$

where $\hat{\sigma}^2 = (1/n) \sum_i \hat{u}_i^2$, $\hat{u}_i$ are the residuals estimated under either the null model or the unrestricted Robinson's model. $\tilde{\beta}$ is the estimated parameter vector under the null model, $S_{X^*} = (1/n) \sum_i X_i^* X_i^{*'}$, and $\tilde{Z}_i' = [1, Z_i']$. Robinson (1988) suggests rejecting the null if the proposed test statistic exceeds the $100(1-\alpha)$th percentile of the χ_k^2 distribution. Alternatively, following Li and Racine (2010), we advocate the residual-based wild bootstrap method to approximate the null distribution of $\hat{T}_n$. The re-sampling procedure is implemented in the following steps:

Step 1: Estimate the null model, and obtain the residuals, $\hat{u}_i$. The wild bootstrap error u_i^* is generated by replacing $\hat{u}_i$ by $[(1-\sqrt{5})/2]\hat{u}_i$ with probability $(1+\sqrt{5})/(2\sqrt{5})$, and by $[(1+\sqrt{5})/2]\hat{u}_i$ with probability $(\sqrt{5}-1)/(2\sqrt{5})$.

Step 2: Generate $Y_i^* = \tilde{Y}_i + u_i^*$, where $\tilde{Y}_i =$ are the fitted values estimated from the null model. Call $\{X_i, Y_i^*, Z_i\}_{i=1}^n$ the bootstrap sample.

Step 3: Use the bootstrap sample to estimate β under the null and the alternative, and obtain residuals $\hat{u}_i^*$ from the unrestricted model, which can be used to estimate σ^2.

Step 4: The bootstrap test statistic $\hat{T}_n^*$ can then be calculated from (25), replacing $\hat{\sigma}^2$, $\hat{\beta}$, and $\tilde{\beta}$ by their bootstrap estimates from Step 3.

Step 5: Repeat Steps 1-4 a large number of times, say $B = 399$ times, and calculate the

p-value: $p = \frac{1}{B}\sum_{b=1}^{B} \mathbf{I}(\hat{T}_n^* > \hat{T}_n)$, where $\mathbf{I}(\cdot)$ is the indicator function with a value of 1 if the statement in the parenthesis is true. The null hypothesis can be rejected if the p-value is less than the level of significance, say 0.05.

B.2 Semiparametric smooth coefficient versus OLS estimator

In this section, we describe the procedure of testing semiparametric smooth coefficient versus OLS estimator. Explicitly, we would like to test the null hypothesis that each regression coefficient in (14) is a linear parametric function of Z_i, i.e., $H_0 : \theta(Z_i) = \theta_0 + Z_i'\theta_1$ and $\beta_m(Z_i) = \beta_{0m} + Z_i'\beta_{1m}, \forall m = 1, \ldots, k$. To perform the test, we follow Li and Racine (2010) to construct the specification test statistic:

$$\hat{I}_n = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j\neq i}^{n} W_i' W_j \hat{u}_i \hat{u}_j K\left(\frac{Z_i - Z_j}{h}\right) \tag{26}$$

where $K(\cdot)$ is the product kernel function, $\hat{u}_i$ is obtained from the fully parametric null model. We follow Li and Racine's (2010) residual-based wild bootstrap method to determine whether to reject the null hypothesis or not:

Step 1: Estimate the null model, obtain fitted values and residuals, and generate wild bootstrap disturbance.

Step 2: Generate the bootstrap sample $\{X_i, Y_i^*, Z_i\}_{i=1}^n$, where Y_i^* is the fitted values under the null plus the generated wild bootstrap disturbance from Step 1.

Step 3: Use the bootstrap sample to estimate the fully parametric model under the null, and obtain residuals;

Step 4: The bootstrap statistic $\hat{I}_n^*$ is obtained from (26), replacing $\hat{u}_i\hat{u}_j$ by their bootstrap estimates from Step 3.

Step 5: Repeat Steps 1-4 a large number of times, say $B = 399$ times, and calculate the p-value: $p = \frac{1}{B}\sum_{b=1}^{B} \mathbf{I}(\hat{I}_n^* > \hat{I}_n)$, where $\mathbf{I}(\cdot)$ is the indicator function with a value of 1 if the statement in the parenthesis is true. The null hypothesis can be rejected if the p-value is less than the level of significance, say 0.05.