Quantifying The Impact of Red Tape on Investment: A Survey Data Approach

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Abstract

An important strand of research in macrofinance investigates which factors impede enterprise investment, and quantifies their aggregate cost. In this paper, we make two contributions to this literature. The first contribution is methodological: we introduce a novel framework to calibrate macroeconomic models with firm-level distortions using enterprise survey micro-data. The core of our innovation is to explicitly model the firms' decisions to report the distortions they face in the survey. Our second contribution is to apply our method across eighty-five countries to characterize the distribution of these distortions and estimate the GDP loss induced by distortionary red tape. Our estimates are based on a dynamic general equilibrium model with heterogenous firms whose capital investment decisions are distorted by red tape. We find that the aggregate cost of red tape varies widely across the countries in our dataset, with an average of 1.8 to 2.1% of GDP and a total of 1.6 trillion dollars. Our framework opens up a new range of applications for enterprise surveys in macro-financial modeling and policy analysis.

JEL Codes: C83, E2, E6, G38, H1, H2, K2, O1, O4
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1. Introduction

Understanding what keeps markets from allocating resources efficiently is a key research question in economics. A recent literature (Hsieh and Klenow, 2009; Baqaee and Farhi, 2020), inspired by earlier work by Harberger (1954), shows that it is possible to approximate the economic cost of the misallocation of production factors among firms, by measuring the cross-sectional dispersion of firms' markups or revenue productivity (TFPR). It is generally understood that this cost of is large (over 20% of GDP), and that it is higher for emerging economies. Yet, what causes this huge factor misallocation is still very much an open question.

Some studies have shown that information frictions (David, Hopenhayn, and Venkateswaran, 2016), adjustment costs (Asker, Collard-Wexler, and De Loecker, 2014), as well as a variety of country-specific firm size distortions (Gourio and Roys, 2014) are all likely to play a role. However, as shown by David and Venkateswaran (2019), a significant proportion of the variation in revenue productivity and – in particular – in the marginal revenue product of capital (a component of revenue productivity) remains to be explained. This is especially true in the case of emerging economies. Particularly difficult to measure is the impact of institutional factors, such as the quality of the regulatory environment.

In this paper, we seek to make two contributions. The first is methodological. We first propose a novel approach to estimate the distortionary impact of *specific* distortions on firm-level investment and factor (mis)allocation. The approach that we propose consists in combining a heterogeneous firms, dynamic general equilibrium model with enterprise survey data. The cornerstone of our methodological contribution is to explicitly model the firms' decision to report the distortions in the survey. This allows us to parametrize the model using moments of the joint distribution of enterprise financials and survey data.

Our second contribution is to then apply our method to estimate the economic cost of red tape (bureaucracy and regulation that delay or constrain investment) across 85 countries. We estimate that, across the 85 countries in our dataset, the economic cost of red tape tops US$ 1.6 trillion. When computed at the country level, as a percentage of GDP, the cost of red tape varies widely across countries: it can be as low as 0.78% of GDP, as in Australia, or as high as 9% of GDP, as in Mozambique.

While this is surely not the first paper to use survey data, and there are many institutions that run firm surveys on a regular basis, this is (to the best of our knowledge) the first paper to embed the firm's survey reporting decision in a general equilibrium model and to use the survey data to discipline the model. What this buys us in practice is the ability to produce a dollar estimate of the economic cost of red tape for a large set of countries.

A key advantage of our approach is that, unlike previous methods, it allows specifically for measurement error contaminating empirical estimates of marginal revenue products. Unlike first-generation studies of factor misallocation (Hsieh and Klenow, 2009; Baqaee and Farhi, 2020), in which measurement error in revenue productivity and markups biases upwards the measured deadweight losses, our approach is conservative, and can attribute variation in revenue productivity and markups to specific frictions (Haltiwanger et al., 2018). The obvious pitfall is that it requires the availability of balance sheet as well as enterprise survey data. Fortunately, this type of dataset is becoming increasingly available to researchers.

We believe that measuring the aggregate economic cost of red tape is an important research question in its own regard. Bureaucracy and regulations have long been argued to cause under-investment and capital misallocation (Posner, 1975; Gray, 1987). Yet, there is a dearth of studies dedicated to measuring aggregate distortionary impact of (broadly defined) red tape on investment.

Figure 1: GDP and Capital per Employee v.s. Regulations Index

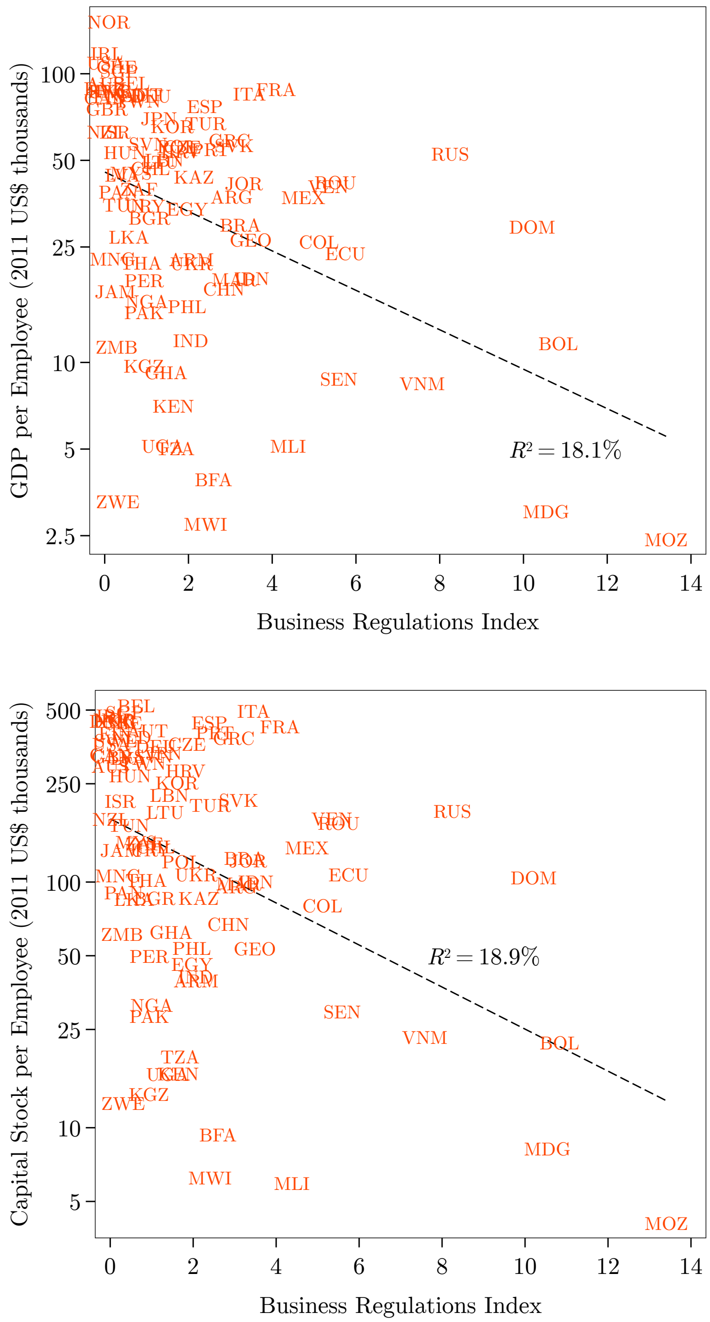

Figure Notes: The figure above plots GDP per employed person (upper panel) and Capital Stock per employed person (lower panel) in 2011 US$ thousands, against an index of business regulations computed from the dataset of Djankov, La Porta, Lopez-de Silanes, and Shleifer (2002). Each observation is a country. The index is the first principal component (in logs) of three variables capturing the average number of days, procedures and steps required to register a new business in the corresponding country. The variables plotted on the vertical axis, which uses a log scale, were obtained from the Penn World Tables v9.1.

To motivate our analysis of the relationship between aggregate investment and red tape, we start from some simple empirical observations, for which we use the dataset of business regulations of Djankov, La Porta, Lopez-de Silanes, and Shleifer (2002, henceforth DLLS). DLLS developed a methodology to measure cross-country differences in the regulatory burden, and showed that countries differ greatly in terms of the red tape faced by their companies.

The upper panel of Figure 1 plots GDP per employee in 2011 US dollars (as measured by the Penn World Tables), against an index of business regulations, which we obtained from the dataset of DLLS. The graph shows a strong negative correlation between these two variables. In the lower panel we replace GDP per employee with capital stock per employee. We find a very similar relationship, except for a much steeper slope – suggesting that the correlation between income and regulation is possibly driven by capital accumulation.

These graphs only present a correlation, of course. What we need in order to estimate the economic cost of red tape is a theoretical framework. For this reason, in the second part of this paper, we propose a dynamic general equilibrium model in which red tape has heterogeneous effects on company investment. We model the impact of bureaucracy as a tax on capital, whose impact varies across firms. Our model incorporates an endogenous saving rate, which allows us to disentangle two margins of the adverse effect of bureaucracy on output. The first is under-investment: by imposing a positive tax on capital, red tape discourages investment across all firms. The second channel is capital misallocation: the cross-sectional heterogeneity in the impact of red tape distorts the allocation of capital among firms.

Our model produces closed-form formulas for the percentage loss in GDP induced by red tape, as well as the percentage change in aggregate TFP. The latter isolates the misallocation channel. Both these formulas depend on a parameter that characterizes the cross-sectional distribution of these wedges.

We then calibrate our model using our survey-based approach. The critical assumption underpinning our calibration strategy is that the capital wedges due to red tape follow a known probability distribution. Given our setting, we make the assumption that these wedges follow a Pareto distribution, which we parametrize using a unique dataset that combines firm-level balance sheet data from the Bureau Van Dijk with survey data. The survey prompts firms to report whether red tape imposes a significant constraint on the company's growth.

The intuition behind our approach is that, to the extent that the survey data correctly identifies firms that are most adversely affected by red tape, we should observe a "shift" in the distribution of the marginal revenue product of capital (MRPK). By effectively measuring the magnitude of this shift, we can parametrize the probability distribution of the wedges. Our model can them inform us how the removing the distortions associated with red tape can boost aggregate productivity and investment.

Finally, we use DLLS's cross-country data to extend this estimation to a total of 85 countries. Based on our model we estimate, for each of those countries, the GDP loss induced by red tape. We find that there is wide variation among countries in the impact of red tape: it ranges from as low as 0.78% of GDP in Australia to as high as 8.86% of GDP in Mozambique. Interestingly, the GDP loss appears to reach significant levels even in developed countries such as France (3.97%).

We find that, for most countries, the aggregate TFP loss is a small share of the overall GDP loss; in other words, most of the GDP losses occur due to lower aggregate saving, rather than capital misallocation.

Our paper brings together different literatures in macroeconomics and finance. First, we contribute from a methodological standpoint to the literatures of financial frictions, under-investment and growth (Beck et al., 2005; Buera et al., 2013; Moll, 2014; Restuccia and Rogerson, 2017) as well as the literature on capital misallocation (Harberger, 1954; Gopinath et al., 2017; David and Venkateswaran, 2019; Baqaee and Farhi, 2020), by showing how red tape can act as a drag on capital investment and allocation and by quantifying this effect.

Second, we contribute to the literature on the effects of regulation and red tape on growth (La Porta et al., 1999; Djankov et al., 2002; Coffey et al., 2020). Our innovation with respect to this literature is to provide a heterogeneous firms modeling framework that allows us to perform counterfactual exercises for a wide set of countries. Previous studies (Klapper et al., 2006; Ciccone and Papaioannou, 2007) have shown that red tape lowers aggregate productivity by delaying the entry of the most productive firms and reducing intersectoral factor reallocation. Our study shows that red tape impacts growth also through under-investment and capital misallocation among incumbents. Though our paper focuses on the impact of red tape on firms' investment, our work is also related to studies that have estimated the impact of red tape on labor allocation and labor productivity (Bertrand and Kramarz, 2002; Kaplan et al., 2007; Ebell and Haefke, 2009).

We also contribute to the large literature on cross-country differences in income and institutions (Hall and Jones, 1999; McGrattan and Schmitz Jr, 1999; Barseghyan, 2008; Égert, 2016), by showing how distortions of firms' investment decision and resource misallocation act as important channels that mediate the effect of institutions on growth (Williamson, 2000; Alesina et al., 2005).

This paper also relates to a growing literature in economics and finance that utilizes enterprise surveys (see for example Ma et al., 2020) to parametrize macroeconomic models with frictions. We believe that the approach developed in this paper can be used to estimate the effect of other frictions. One way to expand this line of research which we see as particularly promising, is to design novel enterprise surveys that are built specifically to calibrate general equilibrium models with firm-level frictions. Central Banks and Censuses (who manage business registry data and run enterprise surveys on a recurrent basis) are among the entities that can most easily accomplish this. We believe that having a quantitative framework in place to take advantage of firm-level survey data can provide valuable guidance on how to design enterprise surveys for maximum robustness and statistical power.

Finally, our methodology for incorporating survey evidence into the estimation of economic models is well-suited to take advantage of a growing wealth of survey data in finance. In addition to long-running surveys of consumer expectations (University of Michigan, 2021) and managerial forecasts (Federal Reserve Bank of Richmond, 2021), new initiatives have begun which survey institutional investors (Giglio et al., 2021). Our framework is portable and general enough to be mapped into these settings and address other long-standing questions.

The rest of the paper is organized as follows: in Section 2 we introduce our framework to leverage survey data to measure firm-level distortions; in Section 3 we introduce the data we use and show how we apply this framework to estimate aggregate cost of red tape; in Section 4 we outline the DGE model that underlies our measurements; in Section 5 we presents the results of this exercise; in Section 6 we discuss their robustness and sensitivity to various assumptions; in Section 7, we conclude.

2. Firm Surveys and Distortions: a Measurement Framework

Consider a model economy that is in a static or steady-state equilibrium, with a set of active firms indexed by $i \in \mathcal{I}$. The starting point of our analysis is the profit-maximization problem of a generic firm i, which combines a vector of inputs $\mathbf{x}_i$ to produce output y_i using some increasing convex function $y(\cdot)$:

$$y_i \; = \; y(\mathbf{x}_i) \tag{2.1}$$

Firm i acts as a price-taker in input markets, charges unit price $p_i(y_i)$ and faces a multiplicative wedge $\exp(\tau_i)$, which is applied to the expenditure on some generic input X. Hence, the optimality condition of firm i with respect to input X takes the form:

$$\mathrm{MRPX}_i \stackrel{\mathrm{def}}{=} \frac{\mathrm{d}\, p_i y_i}{\mathrm{d}\, x_i} \; = \; p^X \cdot \exp(\tau_i) \tag{2.2}$$

where MRPX_i is the Marginal Revenue Product of input X; x_i is the amount of input X input supplied, p^X is the input price, which firm i takes as exogenous; and τ_i is a an actual tax or a shadow tax, which is specific to each firm i and therefore distorts the allocation of input X across firms.

We assume that each firm i draws τ_i from some distribution that has probability density function $f(\tau)$, which is defined over a subset of the real line $\mathbb{R}$. By assumption, MRPX_i is decreasing in input X_i. Therefore, ceteris paribus, firms that draw a positive (negative) value of τ acquire less (more) of input X than they would otherwise.

Suppose that we have a fully laid out model for this economy, and that we can write a measure of aggregate output Y (it can also be welfare, or any other statistic of interest for this economy), as a function of a set of model parameters and firm-level observables $\mathcal{O}$, as well as the density f, which is not known:

$$Y = Y(\mathcal{O}, f) \tag{2.3}$$

We are interested in performing counterfactual exercises on f – that is, studying how aggregate output Y responds to shifts of the wedge distribution $f(\tau)$. In order to perform this exercise, we need to estimate f first. Suppose also that an econometrician administers a survey to a sample of firms, asking each firm to quantify the impact of the economic friction τ_i using an ordered categorical variable:

$$D_i \; \in \; \{1, 2, ..., m\} \tag{2.4}$$

The problem at hand is to formulate an empirical strategy to recover the distribution f, based on some available noisy measure of MRPX_i, as well the response data D_i from this survey. The first contribution we make in this paper – which is a methodological contribution – is to provide such an empirical strategy, which we base on: 1) modeling the firms' response to the survey; 2) making a parametric assumption on f.

The fist step consists in modeling the response of firm i to the survey using a threshold rule. We start by constructing a partition $\mathcal{P}$ of the real line $\mathbb{R}$ into $m+1$ contiguous intervals:

$$\begin{aligned} \mathcal{P} \; &= \; \{ \quad \mathcal{P}^{(1)}, \qquad \mathcal{P}^{(2)}, \qquad ..., \qquad \mathcal{P}^{(m)} \quad \} \\ &= \; \{ \left(-\infty, T^{(1)}\right], \; \left(T^{(1)}, T^{(2)}\right], \; ..., \; \left(T^{(m-1)}, +\infty\right) \} \end{aligned} \tag{2.5}$$

Our key assumption is that the firm i's response is characterized by the following rule: firm i returns response $D_i = t$ if and only if τ_i falls in the t^{th} element $\mathcal{P}^{(t)}$ of the of the partition $\mathcal{P}$ – formally:

$$D_i \equiv \sum_{t=1}^{m} t \cdot \mathbb{I}\left\{\tau_i \in \mathcal{P}^{(t)}\right\} \tag{2.6}$$

Intuitively, what we have done is to break the range of possible values of τ_i into a series of "buckets" that correspond to ordered categorical answers that firm i can provide.

The second step is to make a parametric assumption on f – that is, we assume that f has some known functional form and that it is parametrized by a vector θ, which has dimensionality Θ. We can then define the corresponding cumulative distribution function F:

$$F(\tau;\theta) = \int_{-\infty}^{\tau} f(u;\theta)\, du \tag{2.7}$$

as well as M, the conditional expectation function for τ_i, which conditions on the response variable D_i:

$$\mu(t;\theta,T) \stackrel{\text{def}}{=} \mathbb{E}(\tau_i | D_i = t) \tag{2.8}$$

Assume that we observe MRPX with a multiplicative error term, which is assumed to be identically and independently drawn from some distribution with cumulative probability $G(\varepsilon)$, and to be orthogonal to τ_i, so that

$$\log \widehat{\text{MRPX}}_i = \log \text{MRPX}_i + \varepsilon_i = \log p^X + \tau_i + \varepsilon_i \qquad \text{with} \qquad \varepsilon_i \sim iid\, G(\varepsilon) \perp \tau_i \tag{2.9}$$

Define also $\pi^{(t)}$, the percentage of firms responding $D_i = t$

$$\pi^{(t)} \stackrel{\text{def}}{=} \mathbb{P}(D_i = t) \tag{2.10}$$

as well as $\beta^{(t)}$, the conditional mean difference of logMRPX:

$$\beta^{(t)} \stackrel{\text{def}}{=} \mathbb{E}\left(\log \widehat{\text{MRPX}}_i \middle| D_i = t\right) - \mathbb{E}\left(\log \widehat{\text{MRPX}}_i \middle| D_i = t-1\right) \tag{2.11}$$

The sample counterpart of these two statistics – $\hat{\mu}^{(t)}$ and $\hat{\pi}^{(t)}$ – can measured in the data. Then, the orthogonality assumption $\varepsilon_i \perp \tau_i$ implies that the following system of moment equations:

$$\hat{\beta}^{(t)} = \mu(t;\theta,T) - \mu(t-1;\theta,T) \qquad t = 2,...,m \tag{2.12}$$

$$\hat{\pi}^{(t)} = F\left(T^{(t)};\theta\right) - F\left(T^{(t-1)};\theta\right) \qquad t = 1,2,...,m-1 \tag{2.13}$$

where (with some abuse of notation) $T^{(0)} = -\infty$. This system of moment equations can be used to identify the parameters (θ, T). The system above has $2(m-1)$ equations and $(\Theta + m - 1)$ parameters, which include the vector θ and the $m-1$ thresholds $\left(T^{(1)}, T^{(2)}, ..., T^{(m-1)}\right)$.

Naturally, our derivations assume that the parameters of interest are identified. In practice, the necessary assumptions to ensure identification are dictated by the available data, as there is obviously no guarantee that (θ, T) will be identified in practice: whether it will depends on the dimensionality of these two parameter vectors, the specific functional form of $f(\tau)$, and whether P^X is observed, to name just a few examples.

3. Application: Red Tape and Capital Investment

In this section, we apply the framework presented in Section 2 to measuring the economic cost of red tape. We start from describing the data, and we will then move to the practical implementation of our framework.

3.1. Data

3.1.1. Firm-level Data: EFIGE

Our principal data source is EFIGE: a firm-level database that is provided by the Bruxelles-based think tank Bruegel. The dataset contains data for a representative sample of 14,759 manufacturing firms from seven European countries (Austria, France, Germany, Hungary, Italy, Spain, UK).

The dataset is comprised of two parts. The first part is cross-sectional response data from the EFIGE executives survey, which was conducted by the think tank Bruegel in early 2010: firms were asked questions about a wide range of topics, including their organizational structure, ownership, workforce, international activities, and financing. The second part is a firm/year panel of firm financials (including turnover, assets, interest expenditure, profit and labor costs) for the period 2001-2014 merged from the Amadeus dataset, by the Bureau van Dijk.

We use a dummy variable that encodes the firms' answer to a specific question from the EFIGE survey. The specific question is:

E6. Indicate the main factors preventing the growth of your firm:
- ☐ *financial constraints*
- ☐ *labour market regulations*
- ☐ *legislative or bureaucratic restrictions*
- ☐ *lack of management and/or organizational resources*
- ☐ *lack of demand*
- ☐ *other*

This is a multiple-choice question, and our main explanatory variable — the dummy variable *Red Tape* — equals one if the surveyed firm's manager selected option three, indicating that legislative or bureaucratic restrictions were among the main factors preventing their firm's growth. We also encode firms ticking option two as an additional control variable, which we call *Labor Regulations.*

Because the survey asked firms about their activities in 2009, we use 2009 balance sheet data for our firm-level analysis. However, given that 2009 was a recession year, we also check that our main econometric results carry through when we use data for 2008 or 2010, which were expansion years.

The survey portion of the EFIGE dataset comes with sampling weights to ensure the representativeness of the survey sample. Weighting ensures that the in-sample distribution of firms over industries and size classes matches the population's.

Unfortunately, while the weights guarantee representativeness of the survey portion of the dataset, there is a well-known sample selection issue affecting the balance sheet portion of the dataset. The Amadeus database, which is the source of firm financials, has known issues of coverage and sample selection (Kalemli-Ozcan et al., 2015). Specifically, firm financials appear to be missing, for certain countries (Austria, Germany, the UK) in a non-random way.

We are able to address this issue thanks to the fact that the stratification variables (employment size and NACE 2-digit industry) belong to the survey part of the dataset, and are therefore available for all the firms in the sample, regardless of whether BvD financial data for the corresponding firm is available. This allowed us to devise our own weights, which are computed so that, after reweighing our sample reflects the within-country distribution of the *population* of firms over ISIC rev. 3 broad sectors and employment size classes (10-19,20-49,50-250,250+). We are able to obtain the population distribution from the OECD Structural and Demographic Business Statistics (SDBS) dataset.

We use these weights in our robustness checks. Our baseline results hold when we use our weights that account for sample selection in BvD. In our analysis, we also address sample selection in with a second method, using the fact that France, Hungary, Italy and Spain are virtually free from the sample selection problem (coverage in these countries is nearly 100%). Our baseline estimates also hold when we exclude Austria, Germany and the UK from the Sample.

We will model bureaucracy as a shadow tax on capital investment. Hence, our key firm-level variable will be the Marginal Revenue Product of Capital (MRPK), is computed as follows:

$$\widehat{\text{MRPK}}_i \;=\; \frac{\sigma - 1}{\sigma} \cdot \alpha \cdot \frac{\text{Value Added}_i}{\text{Fixed Assets}_i} \tag{3.1}$$

where σ is the absolute value of the firm-level demand elasticity, α is output-capital elasticity and Value Added can be computed as either revenues less intermediate input costs, or as the sum of capital and labor compensation (EBITDA+Labor Costs).

Following the literature, we calibrate $\sigma = 3$ and $\alpha = {}^1\!/_3$ (although, as it will be clear in the empirical section of the paper, these values have no influence our estimate of the wedge distribution).

One important risk in using survey data is that the information contained in the *Red Tape* dummy might contain a significant subjective component: in other words, it is difficult to know ex-ante to what extent the responses to the EFIGE survey reflect objective obstacles faced by firms due to red tape, or simply the management's subjective assessment of said obstacles. For this reason, we validate the *Red Tape* dummy variable against a well-known, objective measure of regulatory burden.

In any case, measurement error will generally tend to decrease the explanatory power of this variable, and we can therefore expect our results to be somewhat conservative.

3.1.2. Country-level Data on Red Tape

In order to validate the EFIGE survey data, as well as to extend our analysis to a larger set of countries that are not covered in the EFIGE dataset, we use international data on the intensity of regulations compiled by Djankov, La Porta, Lopez-de Silanes, and Shleifer (2002). The data set covers 85 countries and quantifies the regulatory burden faced by entrepreneurs who intend to form a new business, in terms of number of procedures and the length of time required to complete them

We use this dataset because it measures red tape across countries with an objective, comparable methodology. The downside is that these measures of regulation are (conceptually) not a perfect match for our model and firm-level data, as neither the model nor the EFIGE survey focus specifically on startups. In order to work with this dataset, we make the explicit assumption that countries that impose more severe constraints on new entrants *also* impose more severe constraints on incumbents. Under this assumption, DLLS's dataset can still serve as a useful proxy. A different way to say this is that we shall use country-level startup regulations as a proxy for business regulations in a more general sense.

To construct the country-level Regulation Index, we take the first principal component of the logarithms of the three main measures from this dataset: (i) the number of formal procedures, (ii) the number of steps, and (iii) the average duration in days. The principal component is a natural choice of methodology because it captures common variation across the three factors. In this way, we can be agnostic as to whether Red Tape disproportionately affects specific measures, and instead focus on the cross-country variation in bureaucratic constraints on entry. Principal component analysis is designed to be done on unbounded variables, whereas the measures in DLLS are positive by nature of their construction. Thus, we take logarithms of the three measures to make the data amenable to our analysis. The three measures are highly correlated within-country, so that first principal component captures over 98 percent of the cross-country variation in the data.

Red tape can potentially affect all three of these measures: therefore, we combine them into a single Regulations Index for our study.

Next, we use the Regulations Index to validate EFIGE's survey data. In Figure 2 compare, for the 7 countries in EFIGE, the percentage of firms reporting Bureaucracy as a significant constraint to firm growth, with the corresponding Regulations Index from DLLS's dataset. The number of observations in the plot is small, but the correlation between these two variables is nearly perfect (the R^2 is 98.5%). This is important for two reasons: first, it is reassuring that EFIGE's survey data correlates with an objective, well-established statistic; second, this tight relationship allows us to predict π_c (the percentage of firms reporting bureaucracy as a constraint) out-of-sample, and this allows us to compute the GDP losses due to red tape not only for the 7 countries in EFIGE, but for all 85 countries included in DLLS.

3.1.3. Country-level Macroeconomic Data

Our model yields a GDP loss in percentage terms. To compute the corresponding dollar loss, we use 2011 PPP$ GDP from the Penn World Table. We also use 2011 capital stock and employees, to create Figure 1.

3.2. Parametric Implementation

We now show how to implement the methodology that we presented in Section 2. Again, the objective is to recover the distribution of wedges $f(\tau)$. To accomplish this, we shall impose some additional assumptions: these additional assumptions shall be guided by the firm-level data we have at our disposal.

We start from a parametric assumption on f. Given that we are using a firm-level dataset that covers multiple countries, and that we want to estimate the effect of red tape for each individual countries, we shall assume a functional form for f that is common across all countries, but with a country-specific parametrization.

Assumption 1. *We assume that, for a firm i located in country c, τ_i is drawn from an exponential distribution with a country-specific shape parameter θ_c. This is equivalent to saying that $\exp(\tau_i)$ follows a Pareto distribution with scale parameter 1:*

$$\tau_i \sim iid\,\mathrm{Exp}(\theta_c) \quad \Longleftrightarrow \quad e^{\tau_i} \sim iid\,\mathrm{Pareto}(\theta_c, 1) \tag{3.2}$$

We use the Exponential/Pareto distribution for third reasons. First, the asymmetric shape of this distribution is consistent with the asymmetric nature of the distortions being studied (red tape) – i.e. it

Figure 2: Regulations and Survey Data

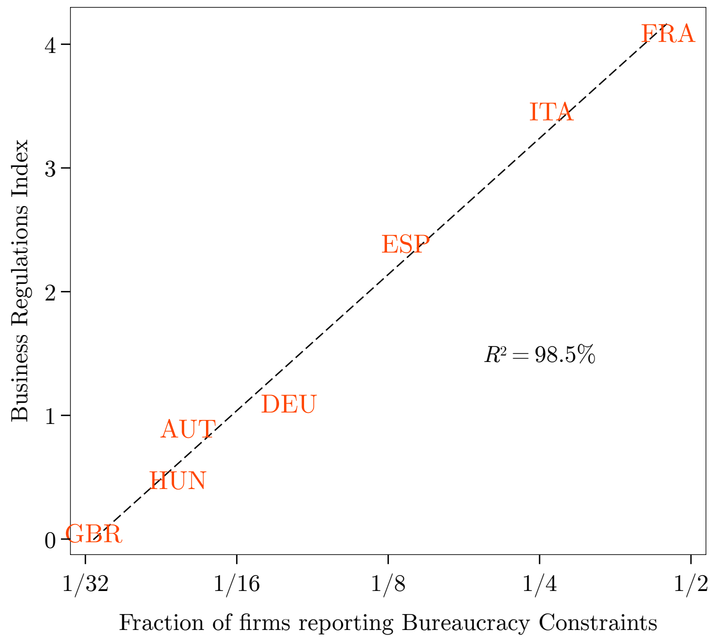

Figure Notes: The figure above plots the probability of a firm reporting bureaucracy as a constraint in the EFIGE survey, by country, against an index of regulatory burden computed from the dataset of Djankov, La Porta, Lopez-de Silanes, and Shleifer (2002). The dotted line is a fitted regression line.

is hard to envision a firm being "facilitated" by red tape[1]. Second, this distribution is also consistent with the asymmetric framing of the survey question used to measure the dummy variable (the question asks to report *constraints* to the growth of the firm). Third, this distribution does not display some undesirable mathematical properties that are typical of the gaussian distribution (the other obvious candidate): we discuss these properties at length in Section 6.

Consistent with our real-life EFIGE survey, firm $i \in c$ is asked to report the burden imposed by red tape in a dummy indicator variable D_i.

Assumption 2. *We assume that D_i takes value 1 if the shadow tax of red tape τ_i overcomes a certain positive reporting threshold T – formally:*

$$D_i \equiv \mathbb{I}\{\tau_i \geq T\} \tag{3.3}$$

we assume this threshold to be uniform across countries.

There are two reasons we assume that the reporting threshold is common across countries. The first is that it reflects the presumption that the survey data is comparable across countries (this was one of the

[1] One could argue of course that bureaucracy hinders some firms to the advantage of some other firms, but this positive effect is already embedded in our model through monopolistic competition structure: firms that draw a lower τ_i benefit from a positive spillover from other firms drawing a higher τ_i, in the former of stronger demand and lower cost of labor. This is an indirect effect, and is not appropriate to model it using a negative wedge.

Figure 3: The Firms' Survey Reporting Decision

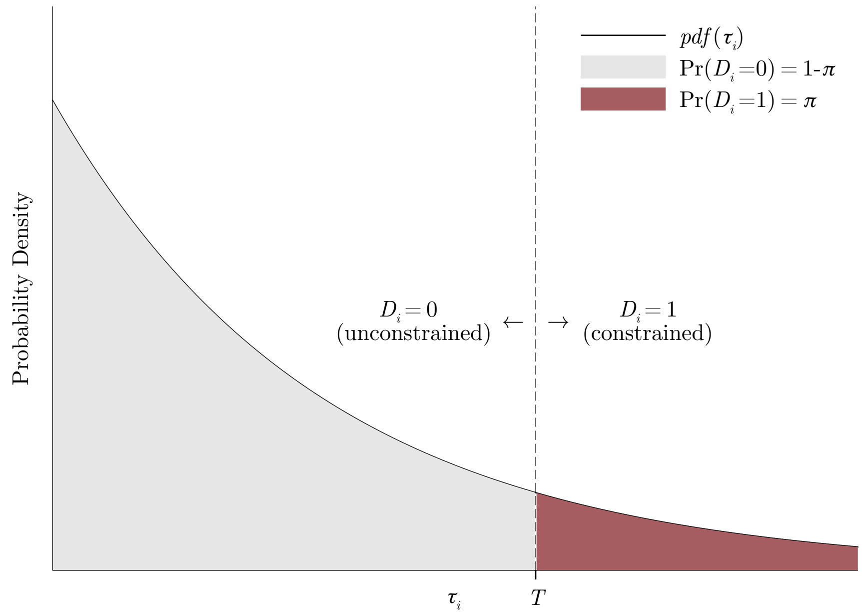

Figure Notes: The above diagram exemplifies firm i's survey reporting decision.

priorities of the architects of the EFIGE survey). Second, this assumption will allow to pool the data across all countries in one single estimation procedure; this will grant us sufficient power to estimate the parameter of interest.

Let π_c be the percentage of firms in country c that report bureaucracy as a constraint to growth:

$$\pi_c \overset{\text{def}}{=} \mathbb{P}\left(D_i = 1 \middle| i \in c\right) \tag{3.4}$$

Figure (3) outlines this setup visually.

Then, assuming that the wedges are exponentially distributed with shape parameter θ_c, we have

$$\pi_c = \exp\left(-\theta_c T\right) \tag{3.5}$$

hence we identify the product $\theta_c T$ as:

$$\theta_c T = -\log\left(\pi_c\right) \tag{3.6}$$

This implies that, conditional on identifying the threshold parameter T, π_c is a sufficient statistic for θ_c.

To identify the threshold parameter T, we use firm i's first order condition for capital, which we augment with an error term to allow for measurement error, in order to capture unobservable variation in MRPK that is unrelated to red tape which we are not modeling explicitly.

Assumption 3. *The Marginal Revenue Product of Capital (MRPK) is observed with a multiplicative error term* $\exp\left(\varepsilon_i\right)$*, that is independently and identically distributed from a distribution with cumulative probability*

G, and is assumed to be statistically independent from the wedge τ_i:

$$\log \widehat{\mathrm{MPRK}}_i \;=\; \log \mathrm{MPRK}_i + \varepsilon_i \qquad \varepsilon_i \sim iid\, G\left(\varepsilon_i\right) \quad \text{and} \quad \varepsilon_i \perp \tau_i \tag{3.7}$$

Assuming that firms behave competitively (except for the capital wedge τ), we then have the following first-order condition for firm i:

$$\log \widehat{\mathrm{MPRK}}_i \;=\; \log r + \tau_i + \varepsilon_i \tag{3.8}$$

where $\widehat{\mathrm{MPRK}}_i$ is the marginal revenue product of capital as measured in the data, and r is the rental rate of capital.

Notice that, had we assumed the absence of measurement error, the observed dispersion in MRPK would have immediately pinned down the distribution of wedges τ_i. There would not have been any need to use survey data, but we would also have been unable to disentangle red tape from any other source of variation in MRPK. Our approach, which allows measurement error and relies on survey data, allows us to avoid attributing all observed variation in MRPK to capital misallocation.

Next, define the following difference in conditional expectations:

$$\beta_c \quad \stackrel{\text{def}}{=} \quad \mathbb{E}\left(\log \widehat{\mathrm{MPRK}}_i \middle| D_i = 1, i \in c\right) \text{-} \mathbb{E}\left(\log \widehat{\mathrm{MPRK}}_i \middle| D_i = 0, i \in c\right) \tag{3.9}$$

As in a regression analysis, an orthogonality condition is required in order to identify θ_c from β_c.

Then, given our previous assumption that τ_i follows an exponential distribution, the conditional "gap" in MRPK between firms that report $D_i = 1$ and those that report $D_0 = 0$, is equal to:

$$\begin{aligned} \beta_c \quad &= \quad \mathbb{E}\left(\tau_i \middle| \tau_i > T \text{ and } i \in c\right) - \mathbb{E}\left(\tau_i \middle| \tau_i < T \text{ and } i \in c\right) \\ &= \quad \frac{T \cdot \exp\left(\theta_c T\right)}{\exp\left(\theta_c T\right) - 1} \quad = \quad \frac{T}{1 - \pi_c} \end{aligned} \tag{3.10}$$

The intuition is that firms that report being constrained by bureaucracy ($\tau_i > 0$) should display a higher marginal revenue product of capital. The width of this gap depends on 1) the reporting threshold T; 2) the shape parameter θ_c, which in turn affects the reporting frequency π_c.

To estimate the reporting threshold T, we run a regression of $\log \mathrm{MRPK}_i$ on the dummy D_i, pooling data from different countries. The resulting pooled slope coefficient β will be equal to a weighted average of the country-level β_c:

$$\beta \quad = \quad \sum_c \omega_c \cdot \beta_c \quad = \quad \sum_c \omega_c \cdot \frac{T}{1 - \pi_c} \tag{3.11}$$

where ω_c is the share of firms in country c:

$$\omega_c \;=\; \mathbb{P}\left(i \in c\right) \tag{3.12}$$

Our assumption that the reporting threshold is constant across countries allows us to take T out of the summation.

$$\beta \;=\; T \cdot \sum_c \frac{\omega_c}{1 - \pi_c} \tag{3.13}$$

Figure 4: Conditional Distribution of MRPK

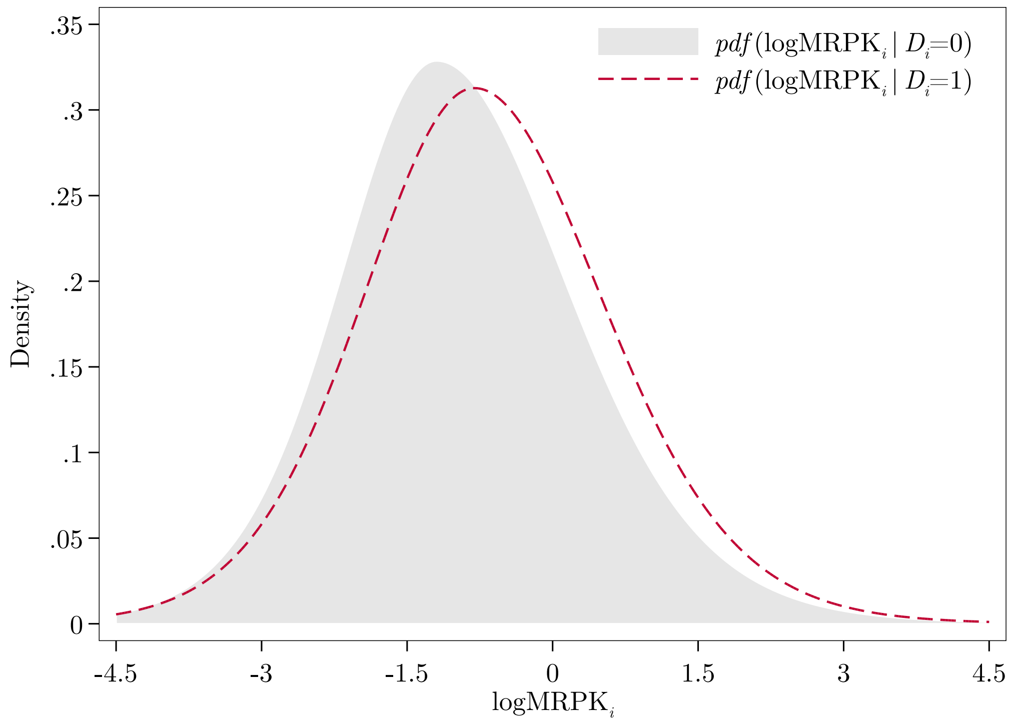

Figure Notes: The figure above plots parametric estimates of the conditional density of the log of Marginal Revenue Product of Capital (MRPK), conditional on the value of the survey dummy in which firms may report bureaucracy as a significant constraint to growth. The grey area is the estimated density for firms that do *not* report bureaucracy as a constraint to growth ($D_i = 0$). The dotted dark line is the estimated density for firms that *do* report bureaucracy as a constraint to growth ($D_i = 1$). The fitted distribution is a 4-parameter Skewed T distribution.

Rearranging this equation allows us to finally identify the reporting threshold T:

$$T \;=\; \frac{\beta}{\sum_c \, \omega_c \, (1 - \pi_c)^{-1}} \tag{3.14}$$

The plan for our empirical analysis is therefore to : 1) Regress $\log \mathrm{MRPK}_i$ on D_i to estimate β; 2) Use equation (3.14) to obtain T; 3) Use π_c and T to obtain estimates of θ_c. Our estimates of θ_c will then be used in the next section to parametrize a dynamic general equilibrium model and compute the GDP loss (gain) from red tape.

3.3. Firm-Level results within the EFIGE sample

For our sample of European firms in the EFIGE sample, we demonstrate that, consistent with our model, firms which report being constrained by bureaucratic red tape in the EFIGE survey also exhibit higher average Marginal Revenue Product of Capital (MRPK) in the BvD financials database. We show this visually in Figure 4, which plots the estimated probability density function of the log of MRPK, conditional on firms' survey responses. The density curve plotted in a dashed line corresponds to those firms that report being

Table 1: MRPK and Red Tape: Regression Analysis

Dependent Variable:	log MRPK						log TFP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Red Tape	0.250*** (0.036)	0.059* (0.035)	0.266*** (0.035)	0.077** (0.034)	0.080** (0.034)	0.065* (0.038)	-0.031 (0.028)
log Age					-0.124*** (0.02)		
Labor Regulations						0.029 (0.037)	
R^2	0.007	0.153	0.058	0.206	0.212	0.207	0.231
Observations	6,895	6,895	6,895	6,895	6,875	6,895	6,895
Country Fixed Effects		✓		✓	✓	✓	✓
Sector Fixed Effects			✓	✓	✓	✓	✓

Table Notes: The table above presents Ordinary Least Squares estimates for the following linear regression model:

$$\log \widehat{\mathrm{MRPK}}_i \;=\; \gamma_c + \varsigma_s + \mathrm{Red\,Tape}_i\,\beta_1 \cdot + \mathbf{x}_i\beta_2 + \varepsilon_i$$

Where $\mathrm{MRPK}_i = \frac{\sigma-1}{\sigma}\alpha\frac{\text{Value Added}_i}{\text{Fixed Assets}_i}$ and α is calibrated to 1/3. Red Tape_i is the EFIGE survey dummy in which firms indicate being constrained by red tape. γ_c andς_s are, respectively, country and sector fixed effects and $\mathbf{x}_i$ is a vector of control variables. Robust standard errors in parentheses: $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

constrained by red tape ($D_i = 1$), while that plotted as a shaded area corresponds to firms that do not report being constrained by red tape ($D_i = 0$). Visual inspection suggests that the MRPK is higher for constrained firms.

We next quantify the magnitude of this shift with a regression analysis. Our specification is

$$\log \widehat{\mathrm{MRPK}}_i \;=\; \gamma_c + \varsigma_s + \mathrm{Red\,Tape}_i\beta_1 \cdot + \mathbf{x}_i\beta_2 + \varepsilon_i \tag{3.15}$$

where Red Tape_i is the EFIGE survey indicator for bureaucratic constraints, and $\mathbf{x}_i$ is a vector of firm i, sector s, and country c characteristics, which we describe in more detail for each regression. We use the *log* of MRPK as a dependent variable; hence, as long as σ and α do not vary systematically within countries/sectors these calibrated values have no effect on our empirical estimates of β, because they are absorbed by the regression fixed effects.

The results of this regression analysis are shown in Table 1. In Column (1), we report the regression results absent any controls, and find a statistically positive regression coefficient of $+0.25$ (significant at the 1% confidence level). When we augment the regression to include country and sector fixed effects, shown in Columns (2) through (4), the sign of the coefficient remains positive but the magnitude decreases to roughly $+0.08$. This implies that the MRPK of a constrained firms about 8 percent higher than that of an otherwise similar unconstrained firm. This magnitude remains stable controlling for addition firm characteristics, such as Firm Age, in column (5). The fact that we are using a regression with country and sector fixed effects implies that we are not relying on country-level variation to identify β.

Because red tape in the general sense is also likely to correlate with labor regulations, we also want to make sure that what we are not inadvertently capturing labor regulations; for this reasons, in column (6) we add, as a control, the dummy variable *Labor Regulations*, which indicates whether the same firm indicated being constrained by labor regulations in the same survey question. Notwithstanding that the correlation between these two variables is high ($\rho = 0.4$), the magnitude of the regression coefficient on *Red Tape* diminishes only marginally after adding this control (+0.065), and remains statistically significant at the 10% confidence level.

Finally, in Column (7), we replace the dependent variable of the regression model (logMRPK) with the log of Total Factor Productivity (TFP), as the dependent variable, in place of log MRPK. We measure TFP as:

$$\mathrm{TFP}_i \;=\; \frac{\text{Value Added}_i^{\frac{\sigma}{\sigma-1}}}{\text{Fixed Assets}_i^{\alpha} \cdot \text{Employees}_i^{1-\alpha}} \tag{3.16}$$

which is consistent with CES demand. The reason we run this additional regression is that it will be important to consider the correlation between TFP and τ_i in calibrating the model. In this specification, we find a slightly negative coefficient on *Red Tape,* that is not statistically different from zero.

Using our model, we can use our regression coefficient estimates, along with country-level data on reporting frequencies, to estimate the T parameter from our model using Equation (3.14). We use our point estimate of $\beta = 0.077$, which implies a value for T of 0.055.

4. A DGE Model of Red Tape and Investment

In this section we present a parsimonious dynamic general equilibrium model that incorporates heterogeneous firm-level investment distortions due to bureaucracy.

The economy features a representative agent with the following utility function:

$$U\left(C_0, C_1, ...\right) \;=\; \sum_{t=0}^{\infty} e^{-\rho t} \cdot u\left(C_t\right) \tag{4.1}$$

The function $u(\cdot)$ increasing, concave and twice differentiable. C_t is the consumption of final good at time t and $\exp(-\rho)$ is the discount rate. The representative agent is endowed with 1 unit of labor which they supply inelastically at a wage rate w_t.

There is a final good producing firm that produces output Y_t, using a CES technology and by taking inputs y_{it} from $i \in [0, 1]$ final good-producing firms:

$$Y_t \;=\; \left(\int_0^1 y_{it}^{\frac{\sigma-1}{\sigma}}\,\mathrm{d}i\right)^{\frac{\sigma}{\sigma-1}} \tag{4.2}$$

The final good firm behaves competitively, hence the price of the final good is:

$$P_t \;=\; \left(\int_0^1 p_{it}^{1-\sigma}\,\mathrm{d}i\right)^{\frac{1}{1-\sigma}} \tag{4.3}$$

and p_i is the price of input i. The intermediate good firms use a Cobb-Douglas production function:

$$y_{it} \;=\; z_i\, k_{it}^{\alpha}\, \ell_{it}^{1-\alpha} \tag{4.4}$$

where k_{it} is capital and ℓ_{it} is labor. Each firm i rents capital and labor from the representative agent at prices r_t and w_t, respectively. We model the effect of red tape as a firm-specific tax on capital τ_i;

$$\pi_{it} \;=\; p_{it} y_{it} - e^{\tau_i} r_t k_{it} - w_t \ell_{it} \tag{4.5}$$

where τ_i is the shadow tax on capital imposed by bureaucracy/red tape. We assume that both the aggregate profits (Π_t) as well as the aggregate tax bill (G_t) are then rebated back to the consumer:

$$\Pi_t \;\stackrel{\text{def}}{=}\; \int_0^1 \pi_{it}\,\mathrm{d}i \qquad \text{and} \qquad G_t \;\stackrel{\text{def}}{=}\; \int_0^1 \left(e^{\tau_i}-1\right) r_{it} k_{it}\,\mathrm{d}i \tag{4.6}$$

The first order conditions for firm i are:

$$\mathrm{MRPK}_{it} \;\stackrel{\text{def}}{=}\; \frac{\sigma-1}{\sigma}\cdot\alpha\cdot\frac{p_{it}y_{it}}{k_{it}} \;=\; e^{\tau_i} r_t \tag{4.7}$$

$$\mathrm{MRPL}_{it} \;\stackrel{\text{def}}{=}\; \frac{\sigma-1}{\sigma}\left(1-\alpha\right)\frac{p_{it}y_{it}}{\ell_{it}} \;=\; w_t \tag{4.8}$$

Let the aggregate capital supply be:

$$K_t \;=\; \int_0^1 k_{it}\,\mathrm{d}i \tag{4.9}$$

Capital depreciates at rate $(1-\delta)$ from period to period, and its evolution is given by the following law of motion:

$$K_{t+1} \;=\; I_t + \delta K_t \tag{4.10}$$

where I_t is aggregate investment, and aggregate consumption is equal to output minus the required investment:

$$\underbrace{P_t Y_t}_{\text{Nominal GDP}} \;=\; P_t\left(C_t + I_t\right) \;=\; \underbrace{r_t K_t + w_t + \Pi_t + G_t}_{\text{Nominal GNI}} \tag{4.11}$$

The consumer's Euler equation is:

$$e^{-\rho}\, u'\left(C_{t+1}\right)\left(\frac{r_{t+1}}{P_{t+1}} + \delta\right) \;=\; u'\left(C_t\right) \tag{4.12}$$

We look for the steady state equilibrium. The Euler equation yields the following long-run equilibrium real interest rate:

$$\frac{r}{P} \;=\; e^{\rho} - \delta \tag{4.13}$$

The firm's first order conditions yield the following steady-state capital-labor ratio:

$$\frac{k_i}{\ell_i} \;=\; \frac{\alpha}{1-\alpha}\cdot\frac{w}{r e^{\tau_i}} \tag{4.14}$$

Demand is isoelastic, therefore firms price at a constant markup over their marginal cost:

$$p_i \;=\; \frac{\sigma}{\sigma-1}\,c_i \tag{4.15}$$

where c_i is firm i's marginal cost, including the wedge on capital (τ_i):

$$c_i \;=\; \frac{1}{z_i}\left(\frac{re^{\tau_i}}{\alpha}\right)^{\alpha}\left(\frac{w}{1-\alpha}\right)^{1-\alpha} \tag{4.16}$$

The firm-level firm-level labor demand:

$$\ell_i \;=\; \frac{z_i^{\sigma-1}\,e^{\alpha(1-\sigma)\tau_i}}{\int_0^1 z_i^{\sigma-1}\,e^{\alpha(1-\sigma)\tau_i}\,\mathrm{d}i} \tag{4.17}$$

Solving for the equilibrium wage yields the firm-level demand for capital and output (we provide these derivations in Appendix B). Aggregating output across firms we obtain GDP as the following expression:

$$Y \;\propto\; \left(\int_0^1 z_i^{\sigma-1}e^{\alpha(1-\sigma)\tau_i}\,\mathrm{d}i\right)^{1/[(\sigma-1)(1-\alpha)]} \tag{4.18}$$

Notice that we can re-write the term in parentheses as an expectation:

$$Y \;\propto\; \left[\mathbb{E}\left(z_i^{\sigma-1}e^{\alpha(1-\sigma)\tau_i}\right)\right]^{1/[(\sigma-1)(1-\alpha)]} \tag{4.19}$$

Following Hsieh and Klenow (2009), and justified by our regression estimates of Table 1, column 7, we make the assumption that τ_i is statistically independent of productivity ($z_i \perp \tau_i$). This allows us to separate expectations and take the log to obtain:

$$\log Y \;=\; \frac{\log\mathbb{E}\left[z_i^{\sigma-1}\right]+\log\mathbb{E}\left[e^{\alpha(1-\sigma)\tau_i}\right]}{(\sigma-1)(1-\alpha)} \;+\; \text{constant} \tag{4.20}$$

Then, using assumption 1, the second expectation in square brackets is simply the $\alpha(1-\sigma)^{th}$ moment of a Pareto-distributed variable, and has a known closed-form solution. Under our parametric assumption, we therefore have the following intuitive expression for aggregate output (per employee):

$$\log Y \;=\; \underbrace{\text{constant}+\frac{\log\mathbb{E}\left(z_i^{\sigma-1}\right)}{(\sigma-1)(1-\alpha)}}_{\text{Undistorted GDP}} \;-\; \underbrace{\frac{\log\left[\theta+\alpha(\sigma-1)\right]-\log\theta}{(\sigma-1)(1-\alpha)}}_{\text{Cost of Red Tape}} \tag{4.21}$$

The equation above implies that, given a parametrization for the triple (σ,α,θ), we can compute the percentage loss of GDP attributable to red tape. Following the literature, we calibrate $\sigma=3$ and $\alpha=1/3$. The procedure outlined in Section 3 allows us to then map our estimates of θ to a percentage reduction in GDP.

There are two mechanisms contributing to lowering aggregate output: the first is a lower savings rate, as bureaucracy lowers the ex-post return on capital. The second effect is a loss in aggregate productivity due to capital misallocation, which is induced by heterogeneity in bureaucracy wedges (Baqaee and Farhi, 2020).

We can isolate the "misallocation" channel by looking at the economy's Total Factor Productivity (TFP):

$$\text{TFP} \stackrel{\text{def}}{=} \frac{Y}{K^\alpha L^{1-\alpha}} \propto \frac{\left[\frac{\theta}{\theta+\alpha(\sigma-1)}\right]^{\frac{1+\alpha(\sigma-1)}{\sigma-1}}}{\left[\frac{\theta}{\theta+1+\alpha(\sigma-1)}\right]^{\alpha}} \tag{4.22}$$

the latter term is the loss in TFP induced by red tape as a function of θ: this expression isolates the capital misallocation effect. This TFP loss can be computed separately for every country, given an estimate of θ.

5. Empirical Results

5.1. Computation of the GDP losses

In this section we present our estimates of the GDP cost of red tape, as implied by our model calibrated using our survey-based procedure. To extend our analysis from the narrow set of countries covered by the EFIGE survey to all 85 countries covered by DLLS's dataset, we estimate a logit model to relate the Business Regulations Index previously constructed to a country-level reporting frequency π_c.

The Regulations Index is the first principal component of three measures capturing the number of procedures, screening time, and registration cost that a start-up must bear before it can operate legally. The first principal component loads equally on all three measures and captures over ninety percent of the cross-sectional variation in the difficult of entry. As seen in Figure 2, the relationship between the Regulations Index and π_c is close to logarithmic for low levels of π_c. Therefore, the logit model is a natural choice for this setting because of its continuous support as well as its bounded range. Using the estimated fit of the logit curve, we can predict the reporting frequency π_c for all 85 countries in DLLS's dataset. This estimate of π_c can then be turned into an estimate of θ_c using equation (3.6).

One potential issue of extrapolating π_c using the Business Regulations index is that it might lead to large prediction errors on π_c at the high end of the distribution, due to the fact that the EFIGE sample was conducted in countries with relatively low and medium values of this Index. Because the (log) GDP loss grows unboundedly as π_c tends to one, this could lead us to over-estimate the GDP loss for countries in the right tail of the distribution. To ensure that the inferred GDP loss remains bounded, even for countries with high Regulation Indices, we put a ceiling to the predicted π_c to 75%, by applying a slight modification to the logit model. Our modified logit specification is:

$$\log \frac{\pi_c}{.75 - \pi_c} = \psi + \phi \cdot \text{Business Regulations}_c + \varepsilon_c \tag{5.1}$$

We first estimate estimate parameters a and b in the subset of countries in the EFIGE survey dataset and then use those fitted parameters to impute country-level reporting frequencies for the larger DLLS sample.

The estimated (modified) logit curve is plotted in Figure 5. In the left panel, we plot the curve together with a scatter plot of the empirical values of the Business Regulation Index against the reporting frequency π_c, for the 7 countries covered by the EFIGE survey. In the right panel, we illustrate where the out-of-sample countries (from the dataset of DLLS) lie along the fitted logit curve. Using the fitted values of the reporting frequencies $\hat{\pi}_c$, together with our estimate of the reporting threshold T, we can compute the parameter θ_c - and with it the GDP loss - for all 85 countries.

Figure 5: Probability of Firm Reporting Bureaucracy as a Constraint

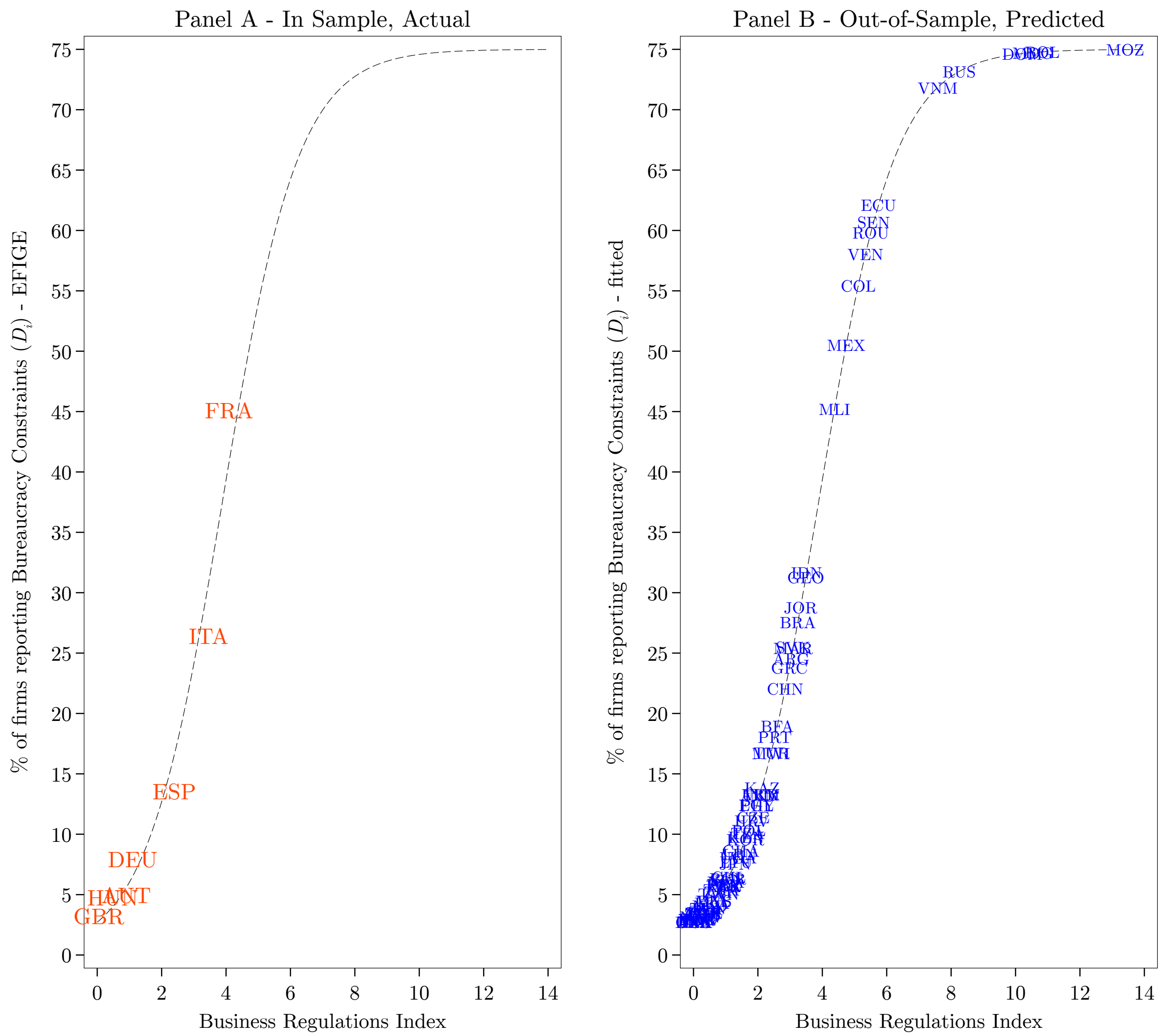

Figure Notes: The figure above plots the probability of a firm reporting bureaucracy as a constraint, by country, against an index of regulatory burden computed from the dataset of Djankov, La Porta, Lopez-de Silanes, and Shleifer (2002, DLLS). The left panel shows the actual percentage of firms whose management indicates Bureaucracy as a major constraint to the firm's growth, as recorded by the EFIGE survey, on the left axis. The dotted line is a fitted logit curve. The right panel shows the probability predicted - out of sample - by the logit fit. These are the countries that are covered by the DLLS dataset but not in EFIGE.

Table 2 shows the results of our calculation. For each country in the DLLS sample, we present estimated output gains, computed using Equation (4.21), as well as the output gains arising solely from improvements in aggregate productivity, computed using Equation (4.22). An important caveat concerning these estimates regards the interpretation. These numbers do not reflect the change in GDP that would occur if red tape were to be removed altogether. In the real world, regulations are not generally introduced with the intention to distort the allocation of resources: they are often there in fact to address market failures. The correct interpretation of these estimates is as the outcome of an informed planner being able to impose a system of subsidies and taxes to rectify the distortions induced by red tape.

We find that red tape imposes a GDP loss of 1.8 to 2.1 percentage of points for the average country (depending on whether we weight by GDP). More importantly, we find that this GDP loss displays a great deal of variation across countries. In countries where the distortionary effect of red tape is minimal, such as Australia or New Zealand, this loss is as low as 0.78% of GDP. In highly-distorted countries, such as Bolivia or Mozambique, the loss approaches 9 percentage points of GDP.

While the most distorted countries are all developing economies, we find that large GDP losses due to red tape are not a unique feature of emerging markets: the distortionary impact of red tape can be significant even in developed countries like France (4.0%).

Totaling up our estimates, we estimate that global output could be increased by at least $1.56 trillion through the removal of the wedges associated with red tape. Furthermore, we see that, while large percentage gains accrue to countries with high Regulations Indices, the bulk of the gains in global GDP arise from large, moderately constrained economies improving their institutions. Global output would increase by over half a trillion dollars if just two countries, China and the Russian Federation, improved their economies by correcting the capital distortions induced by bureaucracy and regulations.

By comparing the overall loss in GDP to the loss arising from lost productivity, we see that a relatively small, but still economically meaningful portion of the GDP gains are attributable to misallocation of resources. For example, 0.71% of the 8.2% of the GDP gains thats we estimate for the Russian Federation stems from reductions in capital misallocation. As seen from Equations (4.21) and (4.22), the decomposition of the GDP gains into gains stemming from capital accumulation versus gains from reallocation are non-linear, and larger gains of reallocation accrue to countries with larger amounts of red tape. For example, in the case of Portugal, the relative share of reallocation gains is an order of magnitude smaller than for the Russian Federation.

6. Robustness and Sensitivity Analysis

We next discuss several factors that could affect the reliability of our estimates and our strategy to address these concerns. We also discuss how sensitive our estimates of the loss in GDP are to variations in our estimates of the coefficient β, which summarizes the firm-level impact of red tape on MRPK.

6.1. Sample Selection

The first source of concern is sample selection. In particular, the balance sheet portion of our firm data is sourced from Bureau van Dijk (BvD). This dataset has known issues of sample selection for a number of countries. Some of them (Austria, Germany, UK) are included in the EFIGE survey. If selection in the sample occurs on variables that correlate with Bureaucracy and such variables and the correlation between MRPK and Bureaucracy varies conditionally on these variables, our estimate for β will be biased.

We can show our estimates are robust to controlling for selection on size and sector. This is because we observe the distribution of firms for sector and employment class variables in the OECD SDBS dataset. In Appendix A, we discuss how we use this data to create a weighting scheme that we use in Appendix D to run a weighted regression that controls for sample selection, ensuring that the analysis sample is representative along these two dimensions. In this specification the estimate for β is shown to increase only slightly.

Table 2: Estimated GDP losses from Red Tape

	GDP Loss from Red Tape				GDP Loss from Red Tape		
Country	US$*bln*	%GDP	Δ%TFP	Country	US$*bln*	%GDP	Δ%TFP
Russian Federation	319.9	8.23	0.72		*(continued)*		
China	263	1.84	0.04	Chile	3.5	1.03	0.01
United States	123.8	0.79	0.01	Austria	3.5	0.97	0.01
India	82.4	1.38	0.02	Sweden	3.3	0.81	0.01
Mexico	76.5	3.97	0.17	Norway	3.2	0.8	0.01
France	76.1	3.06	0.1	Madagascar	3.2	8.77	0.81
Brazil	65.3	2.15	0.05	Peru	3	0.99	0.01
Indonesia	53.3	2.4	0.06	Singapore	2.7	0.85	0.01
Italy	51.4	2.35	0.06	Slovak Republic	2.6	2.03	0.05
Japan	51.2	1.09	0.01	Hong Kong SAR	2.6	0.8	0.01
Vietnam	36.3	7.82	0.65	Mozambique	2.2	8.86	0.83
Germany	36.1	1.03	0.01	Senegal	2.1	5.34	0.31
Venezuela	27.1	4.93	0.26	Denmark	2	0.78	0.01
Colombia	26.2	4.57	0.22	Israel	1.9	0.83	0.01
Turkey	23.3	1.56	0.03	Hungary	1.9	0.87	0.01
Spain	23	1.55	0.03	Ireland	1.8	0.79	0.01
Romania	19.4	5.2	0.29	Jordan	1.8	2.22	0.05
Korea, Rep.	19.3	1.2	0.02	Sri Lanka	1.7	0.9	0.01
United Kingdom	17.8	0.79	0.01	Finland	1.7	0.8	0.01
Argentina	14.3	1.98	0.04	Kenya	1.4	1.21	0.02
Egypt, Arab Rep.	12.2	1.34	0.02	Ghana	1.3	1.15	0.01
Canada	11.4	0.78	0.01	Tanzania	1.3	1.22	0.02
Dominican Republic	11.2	8.74	0.8	Bulgaria	1.2	1.02	0.01
Poland	10.8	1.24	0.02	Croatia	1.1	1.28	0.02
Ecuador	9	5.59	0.33	New Zealand	1.1	0.78	0.01
Thailand	8.7	0.97	0.01	Mali	1	3.44	0.13
Nigeria	8.5	1	0.01	Tunisia	1	0.87	0.01
Taiwan, China	8.5	0.94	0.01	Georgia	0.9	2.38	0.06
Australia	8.2	0.78	0.01	Lebanon	0.9	1.13	0.01
Pakistan	7.8	0.99	0.01	Uganda	0.7	1.12	0.01
Philippines	7.5	1.34	0.02	Lithuania	0.7	1.1	0.01
Netherlands	6.7	0.88	0.01	Uruguay	0.6	0.99	0.01
Ukraine	6.3	1.39	0.02	Slovenia	0.6	1.01	0.01
South Africa	5.9	0.95	0.01	Panama	0.5	0.84	0.01
Greece	5.3	1.94	0.04	Zambia	0.4	0.83	0.01
Malaysia	5.3	0.91	0.01	Armenia	0.4	1.39	0.02
Kazakhstan	5.2	1.42	0.02	Burkina Faso	0.4	1.68	0.03
Bolivia	5.2	8.79	0.81	Latvia	0.3	0.86	0.01
Morocco	4.9	2.03	0.05	Malawi	0.3	1.56	0.03
Portugal	4.4	1.63	0.03	Kyrgyz Republic	0.2	0.98	0.01
Switzerland	4	0.83	0.01	Mongolia	0.2	0.82	0.01
Belgium	3.9	0.91	0.01	Zimbabwe	0.2	0.84	0.01
Czech Republic	3.7	1.29	0.02	Jamaica	0.2	0.83	0.01

Table Notes: The table above presents our estimates of the GDP cost of red tape based on the Model presented in Section 3. The first column presents the figure in billions of dollars, obtained using 2011 PPP$ GDP from the Penn World Table as the measure of aggregate output. The second column is the loss expressed as a percentage of GDP. The third is the percentage change in TFP alone due to capital misallocation induced by red tape. The Regulations Index constructed from DLLS data was used to predict the percentage of firms reporting bureaucratic constraints for countries not covered by the EFIGE survey.

In order to address more broadly selection on unobservables, we also use a more aggressive specification in which we eliminate from our sample all firms from the three countries (Austria, Germany and UK) that are affected by the sample selection problem. In this specification, also shown in Appendix D, the estimate for β is only slightly smaller.

6.2. Cyclicality

A shortcoming of our data is that the EFIGE survey was run at the beginning of 2010, following what was a recession year for the EU. While we do not use time variation to estimate the parameter β, it is natural to wonder whether cyclical effects impact our estimates in some way. In Appendix D, we therefore run additional regressions where the left hand side variable is the log of MRPK computed using data from 2008 and 2010, respectively (GDP growth was positive in the EU in both years). While we *do* expect a smaller β due to the fact that balance sheet and survey data belong to different years, the estimates from these specifications (0.066) are only slightly different from our benchmark estimate, showing that the recession does not seem to be driving our results.

6.3. Production Function Mis-specification

The next issue we want to address is that of production function mis-specification. Our computation of MRPK is based on the assumption of a Value Added based production function (i.e. value added is the measure of nominal output). To ensure that the correlation between MRPK and Red Tape is not sensitive to this assumption, we also compute MRPK based on the assumption an output production function (where revenues are the numerator). In Appendix D, we re-run our benchmark regression using this alternative estimate, and again show that our estimate of β is only marginally affected.

6.4. Model Misspecification

Another possibility that our economic model of red tape as a tax might be mis-specified. To be more specific, we wonder how our estimates might change if Red Tape was not best modeled as a tax on capital, but rather as a tax on output or labor. If this was the case, the effect of the shadow tax would *not* only manifest on MRPK, but also of markups, or the marginal revenue product of labor (MRPL), depending on what inputs are affected. In order to account for this possibility, we compute the marginal revenue product of labor (MRPL) and markups using the method of De Loecker and Warzynski (2012). In Appendix D, re-run our main regression analysis using markups and MPRL as the left-hand side variables in place of MRPK.[2]

We show that Red Tape does not shift the conditional distribution of MRPL or markups significantly; this is consistent with the view that red tape is likely more accurately modeled as a shadow tax on capital rather than as a shadow tax on output or labor.

6.5. Sensitivity Analysis

How sensible are our estimates of the GDP cost of red tape to our estimate of β (the conditional expected log difference in MRPK between constrained and unconstrained firms)?

[2]This specification accounts for the critique of Bond, Hashemi, Kaplan, and Zoch (2020) to the markups estimation technique of De Loecker and Warzynski (2012).

In Appendix E, we present additional estimates computed under alternative values of β in Appendix. Rather than use an intermediate value of β from Table 1, we use a higher and lower value and repeat the procedure of estimating output and TFP. When we assume a β of 0.10, corresponding to a shadow tax of 10% between the average constrained and unconstrained firm, our estimate of global output gains increases from \$2 trillion to \$2.6 trillion. Symmetrically, a value 0.06 for β would lead us to predict output gains of \$1.7 trillion. We emphasize two takeaways from this robustness analysis. Firstly, the gains of eliminating red tape and over-regulation are significant even if shadow taxes are twenty percent lower than our preferred point estimate. Secondly, the gains are roughly unit elastic in the shadow tax, so that a twenty percent change results in approximately a twenty percent change in the expected output gains.

6.6. Alternative Dataset

Finally, in Appendix D, we present estimates computed using an alternative data source. We make use of the World Bank Enterprise Survey, which contains establishment level survey and financial data. We make use of survey questions "j.30c" and "l.30a", which solicit the degree to which licensing and labor regulations, respectively, impede business operations. The survey allows respondents to rank the severity of the impediment on a scale from 0 through 4. We define dummy variables analogous to those in the EFIGE dataset by treating survey responses of 3 and 4, denoting "Major obstacle" and "Very severe obstacle", as indicating that the firm is constrained by bureaucratic and labor regulations.

Our estimates of the economic costs of red tape are economically significant using this alternative dataset. However, we caution that estimates derived from World Bank data are not directly comparable to those derived from EFIGE data due to differing survey methodologies. For one, the World Bank survey question that we use to construct our indicator of bureaucratic constraints asks only about licensing regulations, rather than being an all-inclusive category for bureaucratic regulation as in the EFIGE survey. Another difference is that the World Bank data survey structure differs from that of EFIGE. In the World Bank survey, firms are sequentially asked about a list of twenty potential factors impeding business operations. In the EFIGE survey, on the other hand, firms are asked to name major factors and the indicator variables denote identified constraints. Intuitively, there is a methodological distinction between prompted and unprompted identification of institutional constraints. While these differences make quantitative comparisons challenging, the economic cost of red tape remains large.

6.7. Distributional Assumption: Further Discussion

In mapping the EFIGE survey responses to our model, we made the choice to model the the firm-level cost of red tape using an exponential distribution. While the exponential distribution is no-doubt familiar to many readers, its choice may seem somewhat arbitrary. In this section, we discuss our motivation in choosing this parametrization. The motivations are twofold.

Firstly, we believe that the asymmetric nature is a good match for the survey data that is available to us. To be more specific, both EFIGE and WBES ask firms to report the degree to which they are constrained by red tape; there is no response which allows the firm to indicate that, rather than constrained by red tape, it is abetted by regulation. Indeed, it would be a surprising response to hear a manager indicate the latter. An asymmetric distribution such as the exponential captures this well. Of course, not every survey response in every survey will exhibit such asymmetry, we merely believe that our choice is a natural one given our specific survey.

Our second motivation is that other distributions – including the gaussian distribution – produce the implausible result that equilibrium aggregate output and investment are increasing in the dispersion of the wedges τ_i. A similarly-counterintuitive result has been previously documented in the literature on real options and uncertainty checks, and is known as the Oi (1961)-Hartman (1972)-Abel (1983) effect. Here, we briefly summarize how it applies to our setting qualitatively and then more rigorously.

Firms are able to respond to shadow taxes by adjusting their capital stock. Because these firms face downwards-sloping demand, the reduction in output leads a less than one-for-one reduction in firm profits. In this way, holding fixed the price of capital, the introduction of heterogeneous taxes need not reduce aggregate profits. Given these higher profits, standard assumptions regarding the investment technology will lead to higher investment and a commensurately higher steady-state capital stock.

Everything we have said so far applies in partial equilibrium with a fixed price of capital. In general equilibrium, this effect interacts with the market-clearing condition for capital in two key ways. First, in an economy with cross-sectional heterogeneity in taxes, the price of capital adjusts such that, relative to the undistorted benchmark, some firms effectively receive subsidies and others face taxes. Even if the distribution of taxes is such that every firm faces a non-positive tax, in equilibrium some firms are effectively receiving subsidies because the tax they face is lower in magnitude than the weighted average tax in the economy. Second, the market clearing wage is affected by the distribution of wedges as well.

As a final theoretical point, we emphasize that these effects arise through the investment channel, rather than through aggregate productivity. In our setting, as is typical of the misallocation literature, mean-preserving spreads of the distribution of taxes reduce aggregate productivity. In a static setting with a fixed supply of capital, the investment channel is suppressed, and the only role is that of the reduction in allocative efficiency. It is only when considering the dynamic impact of heterogeneous wedges that dispersion can improve aggregate output.

Crucially for us, assuming that the wedges τ_i follow an exponential distribution results in an economy that does exhibit the Oi-Hartman-Abel effect. The opposite would be the case if we assumed instead that τ_i follows a normal distribution. To see this, recall that, relative to the undistorted benchmark, the change in output respects:

$$\Delta \log Y \ \propto\ -\log \mathbb{E}\left[e^{\alpha(1-\sigma)\tau_i}\right] \tag{6.1}$$

Modeling τ_i as a normally distributed with parameters $N\left(0, \vartheta^2\right)$, we can evaluate the expression above to obtain.

$$\log \mathbb{E}\left[e^{\alpha(1-\sigma)\tau_i}\right] \ =\ \frac{\left[\alpha\left(1-\sigma\right)\vartheta\right]^2}{2} > 0 \tag{6.2}$$

Hence, assuming that τ_i is normal results in an economy which exhibits the Oi-Hartman-Abel effect. In contrast, from Equation 4.21, we see that the exponential distribution assumption gives an unambiguous result that increased dispersion, corresponding to higher θ, reduces output. In Appendix C, we decompose the impact of our distributional assumptions using cumulants to highlight the role of higher order moments of the distribution of wedges in determining the long-run impact of red tape on investment.

7. Conclusions

In this paper, we have proposed a novel measurement framework that leverages enterprise survey data to study the effect of specific policy frictions on firms.

We have used this framework to calibrate a dynamic general equilibrium model with heterogeneous firms, which was then used to study the distortionary impact of bureaucracy and regulation on capital investment and (mis)allocation. We modeled regulations as firm-specific taxes on capital, and computed the aggregate impact of these taxes on both output as well as total factor productivity. We have then taken our model to the data using linked survey and balance sheet enterprise microdata. This enabled us to identify which firms are relatively constrained, as well as observe the impact of these constraints on their performance.

Combining our firm-level estimates with the dataset of Djankov, La Porta, Lopez-de Silanes, and Shleifer (2002), we were able to estimate the GDP and TFP loss due red tape across 85 countries. We found that red tape leads to a global GDP loss of over $1.56 trillion, but with highly asymmetric effects across countries. Our model allows us to decompose the loss in GDP into two distinct channels: (I) the effects of decreased capital investment (II) the effects of improved allocation of resources. We the first channel produces the majority of the losses.

Our approach for estimating aggregate effects based on micro-data is fairly general and can be applied across a wide sample of surveys. In addition, we believe that our framework can inform the design of future enterprise surveys. Our results highlight the costs of over-regulation, as well as the importance of institutions for growth. In the cross section of nations, we identify a number of countries which can significantly improve their annual economic output by curtailing excessive regulation.

As a final remark, we have used theory and survey data to quantify the effects of a specific friction – namely, bureaucratic restrictions on capital. Much variation in marginal revenue products of capital and labor remains to be explained, and we suggest that future work could extend our analysis to new data, in order to address the impact of a wider range of constraints on the economy.

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Appendix

Quantifying The Impact of Red Tape on Investment: A Survey Data Approach

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A. Sample Selection and Representativeness

In this appendix, we explain how we use Inverse Probability Weighting (IPW) to correct for sample selection in the BvD portion of the EFIGE dataset.

The EFIGE survey was administered and equipped with sampling weights in a way that would ensure that the (weighted) distribution of firms across size (number of employees) and industry matches the one reported by Eurostat for each of the 7 countries in the survey. Yet, the balance sheet part of the dataset nonetheless inherits BvD's known issues of representation and sample selection. Specifically, financial data is missing for a number of firms, for reasons not explicitly stated by the vendor BvD (Kalemli-Ozcan et al., 2015). These observations are dropped in regression analyses that use financial data. This poses a problem of sample selection. This problem is not addressed by the weights provided with the dataset, which ensure representativeness only when survey variables *alone* are analyzed.

The sample selection problem does not affect across all countries equally. It is virtually absent for France, Hungary and Italy (where coverage is about 95%). Coverage is much lower for Austria, Germany and UK (25%) as well as Spain (18%). For Germany and the UK the low coverage is due to missing data from the Amadeus databank. For Spain, instead, the low coverage is due to low response rates to the EFIGE survey questions that we use in the analysis.

While it is obviously impossible to control for selection on unobservables, we develop our own weighting scheme to ensure that we can run additional regressions with a sample that is representative in terms of size and sector (we do so in Appendix B).

We obtain reliable estimates of the exact firm distribution in the 7 countries covered by EFIGE by sector s and employment size class e from the OECD Structural and Demographic Business Statistics (SDBS). We define the probability that a generic firm i from country c belongs to sector s and employment size class e:

$$\mathbb{P}\left[i \in (s \cap e) | \, i \in c\right] \tag{A.1}$$

where e is the class size by employee (10-19; 20-49; 50-249; 250+) and s is the sector. This is the conditional probability that we obtain from the SDBS dataset. We then compute the corresponding statistic for firms that are observed in $\mathcal{D}$, the BvD-augmented version of the EFIGE dataset:

$$\mathbb{P}\left[i \in (s \cap e) | \, i \in (\mathcal{D} \cap c)\right] \tag{A.2}$$

The sample selection-correcting weight for a firm that belongs to sector s and employment class e is then defined as:

$$\omega_{cse} = \frac{\mathbb{P}\left[i \in (s \cap e) | \, i \in c\right]}{\mathbb{P}\left[i \in (s \cap e) | \, i \in (\mathcal{D} \cap c)\right]} \tag{A.3}$$

B. Model Derivations

We start by re-writing the firm level output as:

$$y_i \;=\; z_i \cdot \left(\frac{\alpha}{1-\alpha} \cdot \frac{w}{re^{\tau}}\right)^{\alpha} \cdot \ell_i \tag{B.1}$$

To compute GDP, we now derive the firm-level labor demand:

$$\begin{aligned}
\ell_i \;&=\; \left(\frac{1-\alpha}{\alpha} \cdot \frac{re^{\tau_i}}{w}\right)^{\alpha} \frac{y_i}{z_i} \;=\; \left(\frac{1-\alpha}{\alpha} \cdot \frac{re^{\tau_i}}{w}\right)^{\alpha} \frac{1}{z_i} p_i^{-\sigma} \left(\frac{Y}{P^{-\sigma}}\right) \\
&=\; \left(\frac{1-\alpha}{\alpha} \cdot \frac{re^{\tau_i}}{w}\right)^{\alpha} \frac{1}{z_i} \left[\frac{\sigma}{\sigma-1} \cdot \frac{1}{z_i} \left(\frac{re^{\tau_i}}{\alpha}\right)^{\alpha} \left(\frac{w}{1-\alpha}\right)^{1-\alpha}\right]^{-\sigma} \left(\frac{Y}{P^{-\sigma}}\right)
\end{aligned} \tag{B.2}$$

because the aggregate labor supply $L = \sum_i \ell_i$ is fixed we can drop the constant terms when computing labor shares:

$$\frac{\ell_i}{L} \;\propto\; \left(\frac{z_i}{e^{\alpha \tau_i}}\right)^{\sigma-1} \tag{B.3}$$

Then, normalizing the labor force to one ($L = 1$) we have the following firm-level labor demand:

$$\ell_i \;=\; \frac{z_i^{\sigma-1}\, e^{\alpha(1-\sigma)\tau_i}}{\int_0^1 z_i^{\sigma-1}\, e^{\alpha(1-\sigma)\tau_i}\, \mathrm{d}i} \tag{B.4}$$

We plug this expression inside equation (B.1) to obtain the steady-state equilibrium output of firm i (in terms of the factor price ratio w/ℓ):

$$y_i \;=\; \left(\frac{w}{r}\right)^{\alpha} \frac{z_i^{\sigma}\, e^{-\alpha\sigma\tau_i}}{\int_0^1 z_i^{\sigma-1} e^{\alpha(1-\sigma)\tau_i}\, \mathrm{d}i} \tag{B.5}$$

We aggregate output across firms to obtain GDP:

$$Y \;=\; \left(\frac{w}{r}\right)^{\alpha} \left[\int_0^1 \left(\frac{z_i^{\sigma}\, e^{-\alpha\sigma\tau_i}}{\int_0^1 z_i^{\sigma-1} e^{\alpha(1-\sigma)\tau_i}\, \mathrm{d}i}\right)^{\frac{\sigma-1}{\sigma}} \mathrm{d}i\right]^{\frac{\sigma}{\sigma-1}} \tag{B.6}$$

This expression simplifies to:

$$Y \;=\; \left(\frac{w}{r}\right)^{\alpha} \left[\int_0^1 z_i^{\sigma-1} e^{\alpha(1-\sigma)\tau_i}\, \mathrm{d}i\right]^{\frac{1}{\sigma-1}} \tag{B.7}$$

To find the steady-state factor price ratio (w/r) we solve for the CES price index (the GDP deflator):

$$\begin{aligned}
P \;&=\; \frac{\sigma}{\sigma-1} \left(\int_0^1 c_i^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \mathrm{d}i \\
&=\; \frac{\sigma}{\sigma-1} \cdot \left(\frac{r}{\alpha}\right)^{\alpha} \left(\frac{w}{1-\alpha}\right)^{1-\alpha} \left(\int_0^1 z_i^{\sigma-1} e^{\alpha(1-\sigma)\tau_i}\, \mathrm{d}i\right)^{\frac{1}{1-\sigma}}
\end{aligned} \tag{B.8}$$

Multiplying each side of this equation by the respective sides of equation (4.13) and rearranging we find:

$$\frac{r}{P} \;=\; \frac{\sigma}{\sigma-1}\cdot\left(\frac{1}{\alpha}\right)^{\alpha}\left(\frac{1}{1-\alpha}\cdot\frac{w}{r}\right)^{1-\alpha}(e^{\rho}-\delta) \tag{B.9}$$

$$\kappa\left(\frac{w}{r}\right)^{1-\alpha} \;=\; \left(\int_0^1 z_i^{\sigma-1}e^{\alpha(1-\sigma)\tau_i}\,\mathrm{d}i\right)^{\frac{1}{\sigma-1}} \tag{B.10}$$

where we define the constant κ as:

$$\kappa \;\stackrel{\text{def}}{=}\; \frac{\sigma}{\sigma-1}\left(\frac{1}{\alpha}\right)^{\alpha}\left(\frac{1}{1-\alpha}\right)^{1-\alpha}(e^{\rho}-\delta) \tag{B.11}$$

Plugging inside the steady-state GDP equation (B.7) we obtain:

$$Y \;=\; \kappa^{\frac{\alpha}{\alpha-1}}\left[\int_0^1 z_i^{\sigma-1}e^{\alpha(1-\sigma)\tau_i}\,\mathrm{d}i\right]^{\frac{1}{(\sigma-1)(1-\alpha)}} \tag{B.12}$$

Notice that we can re-write the term in parentheses as an expectation:

$$Y \;=\; \kappa^{\frac{\alpha}{\alpha-1}}\left[\mathbb{E}\left(z_i^{\sigma-1}e^{\alpha(1-\sigma)\tau_i}\right)\right]^{\frac{1}{(\sigma-1)(1-\alpha)}} \tag{B.13}$$

We make the assumption that τ_i is statistically independent of productivity ($z_i \perp \tau_i$). This allows us to separate expectations:

$$Y \;=\; \kappa^{\frac{\alpha}{\alpha-1}}\left[\mathbb{E}\left(z_i^{\sigma-1}\right)\right]^{\frac{1}{(\sigma-1)(1-\alpha)}}\cdot\left[\mathbb{E}\left(e^{\alpha(1-\sigma)\tau_i}\right)\right]^{\frac{1}{(\sigma-1)(1-\alpha)}} \tag{B.14}$$

To compute Total Factor Productivity, we compute the firm-level demand for capital:

$$k_i \;=\; \frac{\alpha}{1-\alpha}\cdot\left(\frac{w}{r}\right)\cdot\frac{z_i^{\sigma-1}\,e^{[\alpha(1-\sigma)-1]\tau_i}}{\int_0^1 z_i^{\sigma-1}\,e^{\alpha(1-\sigma)\tau_i}\,\mathrm{d}i} \tag{B.15}$$

We then aggregate and separate expectations to obtain the steady-state supply of capital:

$$K \;\propto\; \left(\frac{w}{r}\right)\cdot\frac{\mathbb{E}\left\{e^{[\alpha(1-\sigma)-1]\tau_i}\right\}}{\mathbb{E}\left\{e^{\alpha(1-\sigma)\tau_i}\right\}} \tag{B.16}$$

We finally define Total Factor Productivity (TFP):

$$\text{TFP} \;\stackrel{\text{def}}{=}\; \frac{Y}{K^{\alpha}L^{1-\alpha}} \;\propto\; \left\{\mathbb{E}\left[e^{\alpha(1-\sigma)\tau_i}\right]\right\}^{\frac{1}{\sigma-1}}\frac{\left\{\mathbb{E}\left[e^{\alpha(1-\sigma)\tau_i}\right]\right\}^{\alpha}}{\left\{\mathbb{E}\left[e^{[\alpha(1-\sigma)-1]\tau_i}\right]\right\}^{\alpha}} \;=\; \frac{\left[\frac{\theta}{\theta+\alpha(\sigma-1)}\right]^{\frac{1+\alpha(\sigma-1)}{\sigma-1}}}{\left[\frac{\theta}{\theta+\alpha(\sigma-1)+1}\right]^{\alpha}} \tag{B.17}$$

C. Further Discussion of our Distributional Assumption

In this appendix, we discuss the particular features of the exponential distribution that give rise to the sharp results in our model. We first note that Equation 6.1 is a specific case of the cumulant generating function of τ, evaluated at $\alpha(\sigma-1)$. The cumulant generating function of a distribution can be obtained by taking the natural logarithm of the moment generating function of said distribution. Taking the Maclaurin expansion of Equation 6.1 allows us to express the change in output as a function of cumulants of the distribution.

$$\Delta \log Y = \frac{1}{(\sigma-1)(1-\alpha)} \sum_{n=1}^{\infty} \kappa_n \frac{(\alpha(1-\sigma))^n}{n!} \tag{C.1}$$

It is well known that, for a log-normal distribution, the first and second cumulant are given by the mean and the variance, respectively, and that all higher-order cumulants are zero. In the case of the exponential distribution, all cumulants are non-zero, and can be expressed as

$$\kappa_n = \theta^{-n}(n-1)! \tag{C.2}$$

Substituting this expression back into Equation 6.1, we see that the contribution of all terms of order k and higher is

$$\frac{1}{(\sigma-1)(1-\alpha)} \sum_{n\geq k} \frac{1}{n} \left(\frac{\alpha(1-\sigma)}{\theta}\right)^n \tag{C.3}$$

In the $k=3$ case, this expression simplifies to $\frac{1}{2}\left(-\left(\frac{\alpha(1-\sigma)}{\theta}\right)^2 - 2\left(\frac{\alpha(1-\sigma)}{\theta}\right) - 2\log\left(1-\left(\frac{\alpha(1-\sigma)}{\theta}\right)\right)\right)$. We see that all three terms in this expression are negative for all plausible values of α, σ, and τ, meaning that it is the higher order moments of the exponential distribution that preclude the Oi-Hartman-Abel effect. As a direct consequence, a log-normal distribution of wedges will increase steady-state output, while an exponential distribution of wedges chosen to have the same lower-order contribution will lead to a decrease in steady-state output.

D. Robustness Checks

Table 3: Marginal Revenue Product of Capital and Red Tape: Regression Analysis

Dependent Variable:	logMRPK					logMarkup	logMRPL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Red Tape	0.066**	0.064*	0.110*	0.070**	0.065*	0.015	0.012
	(0.031)	(0.035)	(0.061)	(0.035)	(0.035)	(0.022)	(0.019)
Labor Regulations							
R^2	0.221	0.194	0.196	0.224	0.149	0.156	0.173
Observations	7,569	6,424	6,895	5,734	7,096	6,291	6,983
Country Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Sector Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Robustness	2008 Data	2010 Data	Selection Weights	ex. AT, DE, GB	Output-based		

The table above presents alternative estimates of the benchmark regression (4) from Table (1). Columns (1) and (2) present estimates based on MRPK computed using (respectively) data from 2008 and 2010 instead of 2009. Column (3) presents estimates from using observation weights that correct for sample selection based on size and sector. Column (4) presents an alternative specification that also accounts for sample selection by excluding those countries (Austria, Germany and the UK) for whom sample selection is an issue. Column (5) presents estimates when the numerator in the computation of MPRK is revenue instead of value added. Column (6) presents a "placebo" specification where the dependent variable is the markup, computed using the approach of De Loecker and Warzynski (2012). In particular, the markup is computed as

$$\mu_i = \frac{\partial \log \text{Output}_i}{\partial \log \text{Materials}_i} \cdot \frac{\text{Revenues}_i}{\text{Material Costs}_i} \tag{D.1}$$

The elasticity of output with respect to material inputs is assumed (in line with De Loecker et al., 2020) is to be 0.85, although this elasticity is irrelevant to the regression results since – after taking logs – this elasticity is absorbed by fixed effects. This addresses the critique of Bond, Hashemi, Kaplan, and Zoch (2020). In Column (7)-(8) we use the log marginal product of labor (MRPL) as the dependent variable instead of logMRPK.

E. Parameter Sensitivity

In this Section, we analyze the sensitivity of our estimates of the country-level output gains. Specifically, we examine the sensitivity of our results to different assumptions regarding the within-country dispersion in MRPK. In our setup this dispersion is governed by the parameter β, which we estimate using the Bureau Van Dijk sample. In our main specification, this parameter is estimated to be roughly 0.08, corresponding to an 8 percent high MRPK for constrained versus unconstrained firms. In the following tables, we re-estimate output gains using alternative values of this parameter. Table 4 presents an upper bound on our estimates of the GDP cost of red tape based on the Model presented in Section 3. Rather than use our estimate of $\beta = 0.077$, we use the higher value of $\beta = 0.10$.

Symmetrically, we re-estimate output gains using a lower value of β in Table 5. Rather than use our estimate of $\beta = 0.077$, we use a value of $\beta = 0.06$. In both cases, we see that our results are quantitatively similar. As expected, higher values of β imply greater gains from the removal of red tape, while lower values imply the opposite.

Table 4: Estimated GDP losses from Red Tape, using $\overline{\beta}$

Country	GDP Loss from Red Tape US$*bln*	%GDP	Δ%TFP
Russian Federation	398.5	10.05	1.06
China	328.8	2.29	0.06
United States	153.8	0.98	0.01
India	103	1.72	0.03
Mexico	95.6	4.91	0.26
France	95	3.79	0.16
Brazil	81.6	2.67	0.08
Indonesia	66.6	2.98	0.1
Italy	64.2	2.92	0.09
Japan	63.5	1.35	0.02
Vietnam	45.2	9.56	0.96
Germany	45	1.28	0.02
Venezuela	33.8	6.07	0.39
Colombia	32.6	5.63	0.34
Turkey	29.1	1.94	0.04
Spain	28.8	1.93	0.04
Romania	24.2	6.41	0.44
Korea, Rep.	24.1	1.49	0.02
United Kingdom	22.4	0.99	0.01
Argentina	17.9	2.46	0.07
Egypt, Arab Rep.	15.3	1.67	0.03
Canada	14.4	0.98	0.01
Dominican Republic	13.9	10.65	1.19
Poland	13.5	1.54	0.03
Ecuador	11.2	6.87	0.5
Thailand	10.8	1.2	0.02
Nigeria	10.7	1.25	0.02
Taiwan, China	10.7	1.18	0.02
Australia	10.3	0.98	0.01
Pakistan	9.7	1.23	0.02
Philippines	9.4	1.67	0.03
Netherlands	8.3	1.1	0.01
Ukraine	7.9	1.73	0.03
South Africa	7.4	1.19	0.02
Greece	6.6	2.41	0.06
Malaysia	6.5	1.13	0.01
Kazakhstan	6.5	1.76	0.03
Bolivia	6.4	10.72	1.2
Morocco	6.1	2.52	0.07
Portugal	5.5	2.03	0.05
Switzerland	5	1.04	0.01
Belgium	4.9	1.13	0.01
Czech Republic	4.7	1.61	0.03
(continued)			
Chile	4.4	1.28	0.02
Austria	4.3	1.21	0.02
Sweden	4	1	0.01
Norway	4	1	0.01
Madagascar	4	10.69	1.19
Peru	3.7	1.23	0.02
Singapore	3.4	1.06	0.01
Slovak Republic	3.3	2.52	0.07
Hong Kong SAR	3.2	1	0.01
Mozambique	2.8	10.8	1.22
Senegal	2.6	6.58	0.46
Denmark	2.5	0.98	0.01
Hungary	2.3	1.09	0.01
Israel	2.3	1.03	0.01
Ireland	2.3	0.99	0.01
Jordan	2.2	2.76	0.08
Sri Lanka	2.2	1.12	0.01
Finland	2.1	1	0.01
Kenya	1.7	1.5	0.02
Ghana	1.6	1.43	0.02
Tanzania	1.6	1.52	0.03
Bulgaria	1.4	1.27	0.02
Croatia	1.4	1.59	0.03
New Zealand	1.4	0.98	0.01
Mali	1.3	4.26	0.2
Tunisia	1.2	1.08	0.01
Georgia	1.1	2.95	0.09
Lebanon	1.1	1.41	0.02
Uganda	0.9	1.39	0.02
Lithuania	0.9	1.37	0.02
Uruguay	0.7	1.24	0.02
Slovenia	0.7	1.26	0.02
Panama	0.7	1.05	0.01
Zambia	0.5	1.04	0.01
Armenia	0.5	1.73	0.03
Burkina Faso	0.5	2.09	0.05
Latvia	0.4	1.08	0.01
Malawi	0.3	1.94	0.04
Kyrgyz Republic	0.3	1.23	0.02
Mongolia	0.3	1.02	0.01
Zimbabwe	0.3	1.05	0.01
Jamaica	0.2	1.03	0.01

Table Notes: The table above presents an upper bound on our estimates of the GDP cost of red tape based on the Model presented in Section 3. Rather than use our estimate of $\beta = 0.077$, we use the higher value of $\beta = 0.10$. The first column presents the figure in billions of dollars. The second as a percentage of GDP. The third is the percentage change in TFP alone due to capital misallocation induced by red tape. The Regulations Index constructed from DLLS data was used to predict the percentage of firms reporting bureaucratic constraints for countries not covered by the EFIGE survey.

Table 5: Estimated GDP losses from Red Tape, using $\underline{\beta}$

Country	GDP Loss from Red Tape US\$*bln*	%GDP	Δ%TFP
Russian Federation	241	6.33	0.43
China	197.7	1.39	0.02
United States	92.2	0.59	0
India	61.9	1.04	0.01
Mexico	57.6	3.02	0.1
France	57.3	2.32	0.06
Brazil	49	1.62	0.03
Indonesia	40.2	1.82	0.04
Italy	38.7	1.78	0.03
Japan	38.4	0.82	0.01
Vietnam	27.3	6	0.38
Germany	26.9	0.77	0.01
Venezuela	20.3	3.75	0.15
Colombia	19.7	3.47	0.13
Turkey	17.5	1.18	0.02
Spain	17.3	1.17	0.02
Romania	14.6	3.96	0.17
Korea, Rep.	14.4	0.9	0.01
United Kingdom	13.3	0.59	0
Argentina	10.7	1.49	0.02
Egypt, Arab Rep.	9.2	1.01	0.01
Canada	8.6	0.59	0
Dominican Republic	8.4	6.72	0.48
Poland	8.1	0.93	0.01
Ecuador	6.7	4.26	0.2
Thailand	6.6	0.73	0.01
Taiwan, China	6.4	0.71	0.01
Nigeria	6.4	0.75	0.01
Australia	6.2	0.59	0
Pakistan	5.8	0.74	0.01
Philippines	5.6	1.01	0.01
Netherlands	5	0.66	0
Ukraine	4.7	1.05	0.01
South Africa	4.5	0.72	0.01
Greece	4	1.46	0.02
Malaysia	3.9	0.68	0.01
Kazakhstan	3.9	1.07	0.01
Bolivia	3.9	6.76	0.49
Morocco	3.6	1.53	0.03
Portugal	3.3	1.23	0.02
Switzerland	3	0.63	0
Belgium	2.9	0.68	0.01
Czech Republic	2.8	0.97	0.01

Country	GDP Loss from Red Tape US\$*bln*	%GDP	Δ%TFP
	(continued)		
Chile	2.6	0.77	0.01
Austria	2.6	0.73	0.01
Sweden	2.5	0.61	0
Norway	2.4	0.6	0
Madagascar	2.4	6.75	0.48
Peru	2.2	0.74	0.01
Singapore	2.1	0.64	0
Slovak Republic	2	1.53	0.03
Hong Kong SAR	1.9	0.6	0
Mozambique	1.7	6.82	0.49
Senegal	1.5	4.07	0.18
Denmark	1.5	0.59	0
Hungary	1.4	0.66	0
Israel	1.4	0.62	0
Ireland	1.3	0.59	0
Jordan	1.3	1.68	0.03
Sri Lanka	1.3	0.67	0.01
Finland	1.3	0.6	0
Kenya	1	0.91	0.01
Ghana	0.9	0.86	0.01
Tanzania	0.9	0.92	0.01
Bulgaria	0.9	0.77	0.01
Croatia	0.8	0.96	0.01
New Zealand	0.8	0.59	0
Mali	0.8	2.61	0.07
Tunisia	0.7	0.65	0
Georgia	0.7	1.8	0.04
Lebanon	0.6	0.85	0.01
Uganda	0.5	0.84	0.01
Lithuania	0.5	0.83	0.01
Uruguay	0.4	0.75	0.01
Slovenia	0.4	0.76	0.01
Panama	0.4	0.63	0
Zambia	0.3	0.63	0
Burkina Faso	0.3	1.26	0.02
Armenia	0.3	1.04	0.01
Latvia	0.3	0.65	0
Malawi	0.2	1.18	0.02
Kyrgyz Republic	0.2	0.74	0.01
Mongolia	0.2	0.61	0
Zimbabwe	0.2	0.63	0
Jamaica	0.1	0.62	0

Table Notes: The table above presents an upper bound on our estimates of the GDP cost of red tape based on the Model presented in Section 3. Rather than use our estimate of $\beta = 0.077$, we use a value of $\beta = 0.06$. The first column presents the figure in billions of dollars. The second as a percentage of GDP. The third is the percentage change in TFP alone due to capital misallocation induced by red tape. The Regulations Index constructed from DLLS data was used to predict the percentage of firms reporting bureaucratic constraints for countries not covered by the EFIGE survey.

F. Alternative Dataset: the World Bank Enterprise Survey

In this Section, we report estimates of the GDP cost of red tape where we measure business regulations using the World Bank Enterprise Survey. The survey contains firm-level financials matched to questionnaire responses for a large number of countries. For each surveyed firm, we take latest set of firm financials and match it with the most recent survey responses as of the time of the financials. We take survey question "j30c" to be our measure of regulatory burden. Respondents are asked to indicate, on a scale of 0 to 4, the degree to which business licensing and permits are an obstacle to the current operations of their establishment. We take survey responses of 3 or higher, indicating either a "Major obstacle" or a "Very severe obstacle", as indicating that the firm is constrained by red tape. We take survey question "l30a" to be our measure of labor regulations, and define an analogous dummy variable for labor. We then repeat our analysis using the firm-level financials in the Survey. Because the World Bank data does not report the manufacturing industry of each firm, we include size fixed effects to control for general firm scale. We restrict our sample to manufacturing firms for which the survey provides an estimate of MRPK. Regression evidence of differences in MRPK between constrained and unconstrained firms are reported in Table (6).

Table (7) presents our estimates of the GDP cost of red tape based on the Model presented in Section 3, estimated based on survey responses and firm-level financial data from the World Bank Enterprise Survey. The first column presents the figure in billions of dollars. The second as a percentage of GDP. The third is the percentage change in TFP alone due to capital misallocation induced by red tape.

Table 6: Marginal Revenue Product of Capital and Red Tape: Regression Analysis

Dependent Variable: log MRPK

	(1)	(2)	(3)	(4)
Red Tape	0.103	0.105	0.111	0.137
	(0.078)	(0.074)	(0.083)	(0.084)
Labor Regulations			-0.022	-0.000
			(0.094)	(0.097)
log Age				0.026
				(0.028)
R^2	0.091	0.107	0.107	0.109
Observations	42,600	42,594	42,594	39,750
Year Fixed Effects	✓	✓	✓	✓
Country Fixed Effects	✓	✓	✓	✓
Industry Fixed Effects		✓	✓	✓

Table Notes: The table above presents Ordinary Least Squares estimates for the following linear regression model:

$$\log \text{MRPK}_i \;=\; \gamma_c + \varsigma_s + \varphi_t \text{Red Tape}_i\,\beta_1 \cdot + \mathbf{x}_i \beta_2 + \varepsilon_i$$

Where $\text{MRPK}_i = \frac{\sigma-1}{\sigma}\alpha\frac{\text{Value Added}_i}{\text{Fixed Assets}_i}$ and α is calibrated to 1/3. Red Tape_i is a dummy constructed from World Bank survey question j30c in which firms indicate being constrained by bureaucracy. γ_c, ς_s, and φ_t are, respectively, country, industry, and year fixed effects and $\mathbf{x}_i$ is a vector of control variables. Robust standard errors in parentheses: $^{*}p < .1; ^{**}p < .05; ^{***}p < .01$

Table 7: Estimated GDP losses from Red Tape - estimates based on World Bank Enterprise Survey Data

	GDP Loss from Red Tape				GDP Loss from Red Tape				GDP Loss from Red Tape		
Country	US$*bln*	%GDP	Δ%TFP	Country	US$*bln*	%GDP	Δ%TFP	Country	US$*bln*	%GDP	Δ%TFP
Brazil	183.8	5.82	0.36	Vietnam	4.4	1.02	0.01	Cyprus	0.8	3.19	0.11
Turkey	164.3	10.06	1.05	Ecuador	4	2.55	0.07	Georgia	0.7	1.96	0.04
China	153.2	1.08	0.01	Israel	3.9	1.73	0.03	Albania	0.7	2.38	0.06
India	152.8	2.53	0.07	Burkina Faso	3.6	14.31	2.09	Latvia	0.6	1.64	0.03
Russia	73.9	2.03	0.04	Uzbekistan	3.6	1.74	0.03	Mongolia	0.6	2.37	0.06
Mexico	64	3.34	0.12	Belarus	3.5	1.95	0.04	Guinea	0.6	2.95	0.09
Italy	48.3	2.21	0.05	Kenya	3.5	3.01	0.1	Zimbabwe	0.6	2.43	0.06
Indonesia	45.8	2.07	0.05	Azerbaijan	3.3	2.19	0.05	Gambia, The	0.6	12.4	1.58
Egypt, Arab Rep.	29.2	3.15	0.11	Myanmar	3.3	1.62	0.03	Malawi	0.6	3.28	0.12
Nigeria	21.9	2.52	0.07	Tanzania	3.2	3.06	0.1	Palestine	0.6	2.7	0.08
Slovak Republic	21	14.31	2.09	Guatemala	2.8	2.7	0.08	Chad	0.6	2.31	0.06
Pakistan	20	2.51	0.07	Bulgaria	2.5	2.18	0.05	Moldova	0.5	2.65	0.08
Argentina	19.5	2.67	0.08	Costa Rica	2.5	4.05	0.18	Nicaragua	0.5	2.14	0.05
Dominican Rep.	19.5	14.31	2.09	Yemen, Rep.	2.4	2.33	0.06	Mozambique	0.5	2.15	0.05
Venezuela, RB	18.1	3.35	0.12	Bosnia & H.	2.3	6.06	0.39	Kyrgyz Rep.	0.5	2.15	0.05
Colombia	16.9	2.99	0.1	Ghana	2.1	1.93	0.04	Tajikistan	0.5	2.04	0.05
Ukraine	16.3	3.51	0.13	Cameroon	1.7	2.88	0.09	Jamaica	0.5	2.31	0.06
Iraq	15.6	4.09	0.18	Ethiopia	1.7	1.53	0.03	Armenia	0.4	1.63	0.03
Philippines	13.3	2.35	0.06	Croatia	1.7	1.89	0.04	Suriname	0.4	5.02	0.27
Poland	12.9	1.48	0.02	Lebanon	1.6	2.11	0.05	Estonia	0.4	1.17	0.02
Greece	12.6	4.5	0.22	Uganda	1.6	2.41	0.06	St. Lucia	0.3	14.31	2.09
Malaysia	12.3	2.11	0.05	Tunisia	1.6	1.38	0.02	Niger	0.3	2.31	0.06
Peru	11.2	3.6	0.14	Bolivia	1.5	2.77	0.08	Benin	0.3	1.7	0.03
Sudan	10.7	6.58	0.46	Sierra Leone	1.5	14.31	2.09	Lesotho	0.3	5.29	0.3
Romania	9.9	2.72	0.08	Jordan	1.5	1.88	0.04	Mauritania	0.3	2.29	0.06
Angola	9.6	5.14	0.28	Serbia	1.4	1.47	0.02	Namibia	0.3	1.35	0.02
Thailand	9.3	1.03	0.01	Paraguay	1.2	2.52	0.07	Rwanda	0.2	1.37	0.02
Bangladesh	8.4	1.94	0.04	Honduras	1.2	3.31	0.12	Bahamas, The	0.2	1.83	0.04
Chile	8.2	2.35	0.06	Nepal	1.1	1.87	0.04	Togo	0.2	2.19	0.05
Congo, D.R.	7.4	14.31	2.09	Panama	1.1	1.75	0.03	St. Kitts & N.	0.2	14.31	2.09
Morocco	7	2.89	0.09	Uruguay	1.1	1.85	0.04	Burundi	0.2	2.3	0.06
Trinidad & T.	6.9	14.31	2.09	Senegal	1.1	2.91	0.09	St.Vincent & G.	0.2	14.31	2.09
Kazakhstan	6.9	1.87	0.04	Lithuania	1	1.59	0.03	Montenegro	0.1	1.42	0.02
El Salvador	6.7	14.31	2.09	Botswana	1	3.54	0.14	Malta	0.1	1.16	0.01
Portugal	5.5	2.02	0.04	Slovenia	1	1.72	0.03	Bhutan	0.1	1.95	0.04
Lao PDR	5.2	14.31	2.09	Cambodia	1	2.54	0.07	Liberia	0.1	2.75	0.08
Sweden	5.2	1.27	0.02	Zambia	0.9	2	0.04	Belize	0.1	3.16	0.11
Czech Republic	5.1	1.75	0.03	Madagascar	0.9	2.58	0.07	Antigua & B.	0.1	2.88	0.09
Sri Lanka	5	2.53	0.07	Mali	0.8	2.79	0.08	Grenada	0	1.74	0.03