Indian Labor Regulations and the Cost of Corruption: Evidence from the Firm Size Distribution*

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Abstract

This paper investigates the effects of an important but little-researched set of Indian labor and industrial regulations. We use a novel methodology to provide a) the first objective cost estimates of any Indian labor regulations and b) evidence of their impact on misallocation of resources across firms. Our methodology takes advantage of the fact that some regulations only apply to establishments which hire 10 or more employees. Using data from India's 2005 Economic Census, we observe that the distribution of establishments by size closely follows a power law, but with a significant drop in the distribution for establishments with 10 or more workers. Guided by a model based on Garicano, Lelarge, and Van Reenen (2013) - but augmented to allow for the possibility of misreporting - we use this drop to estimate the implied costs of the regulation. We find that there is substantial variation in our estimated costs across states, industries and ownership types, and that our costs are more robustly correlated with measures of corruption than with any other factors, suggesting that poor state implementation may be as much or more to blame for the high costs than the regulations themselves. We find further that higher costs are associated with lower rates of future employment growth in registered (but not unregistered) manufacturing, suggesting that these costs may play a role in encouraging informality.

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1 Introduction

India's labor and industrial regulations have been blamed for many of the country's ills, including low levels of aggregate productivity, slow growth of productivity, and lackluster job creation in the formal sector[1] (e.g. Hsieh and Klenow (2009); Kochhar, Kumar, Rajan, and Subramanian (2006); Besley and Burgess (2004); Hasan and Jandoc (2012)). Of particular note is Hsieh and Klenow (2009)'s landmark study, in which the authors argue that aggregate total factor productivity in India could be 40%-60% higher if not for significant misallocation of resources across firms. They go on to suggest that India's labor regulations may be to blame for the observed misallocation, although they leave the job of fully corroborating this link to others. In fact, the view that labor regulations are of primary importance is not universally held. Many argue that the laws as written are rarely enforced so that, in practice, firms are effectively unconstrained.[2] Others argue that the existing evidence on the detrimental impact of labor regulations is flawed (Bhattacharjea (2006, 2009)). Still others point out that the vast majority of regulations have gone unstudied while nearly all of the attention from economists and the press has focused on a single regulation (Chapter VB of the Industrial Disputes Act) - one that is not likely to constrain any but the very largest firms (Bardhan (2014)).[3]

It is the goal of this paper to address the above aspects of this debate while avoiding some of the criticisms that have been leveled at previous work. In particular, we use a novel methodology and a uniquely well-suited dataset to study the behavior of firms in response to regulatory thresholds in order to determine whether and to what extent firms are in fact constrained by regulations.[4] We proceed in the following steps. First, we generate the establishment-size distribution using data from the Economic Census of India (EC), which, importantly, aims to be a complete enumeration of *all* non-farm business units, regardless of size or status (formal or informal). From the distribution, we observe that it closely follows a power law, except for a discontinous and proportional decrease in the density of establishments with 10 or more workers. This is precisely the threshold at which a multitude of regulations become legally binding, so we take this observation as evidence that firms with

[1]Here and elsewhere in the paper, the formal sector refers to business enterprises that are registered with some branch of the government.

[2]For instance, in a recent paper, Chaurey (2015) provides evidence that firms seem to hire contract workers as a way of avoiding certain regulations.

[3]Chapter VB of the Industrial Disputes Act (IDA) stipulates that firms in the industrial sector with 100 or more workers must obtain permission from the relevant governmental authority before laying off workers. Bardhan (2014) points out that 92 percent of firms in the garmet sector have less than 8 workers.

[4]Note: for expositional purposes we occasionally refer to "firms", although it would be more correct to refer to "factories" or "establishments", since all of the data and most of the regulations are at the factory/establishment level rather than the firm level. Regardless, the disinction is almost moot: nearly all Indian firms are single factory/establishment firms.

10 or more workers *do* seem to be constrained in size by certain regulations - although these are not the same regulations that most others have focused on. We then develop a model of firm size choice under regulatory thresholds which is based on Garicano et al. (2013) (henceforth GLV), but augmented to explicitly allow for the possibiliy of misreporting.[5] We model the regulations as causing an increase in the unit labor costs of those firms that report having exceeded the 10 worker threshold[6], and then use the observed distortion in the size distribution to estimate these costs. Under our primary estimation method at the All-India level, we find that firms behave as if operating at or above the 10-worker threshold entailed a 35% increase in their per-worker costs.

Our next step is to document substantial heterogeneity in the size of our estimated costs along several dimensions including state, industry and ownership type. For example, we find that the state with the highest estimated regulatory costs is Bihar and that privately-owned establishments have the highest costs, while government-owned establishments have the lowest. Exploring this variation further, we find that our estimated costs turn out to be correlated with some previous state-level measures of labor regulation reforms (in particular, certain measures from Dougherty (2009)), though not with others (for example, the Besley-Burgess measure from Aghion, Burgess, Redding, and Zilibotti (2008)).[7] Moreover, we find strong and robust correlations between our estimated costs and two quite distinct measures of corruption[8], even after controlling for a number of factors including state GDP per capita. As further support for our state-level results, we show that industries with greater "regulatory dependence" have higher estimated costs, but only when they are located in more corrupt states.[9] We take these correlations to be suggestive of the fact that the true cost of the regulations may have more to do with bureacracy and corruption, rather than the content of labor and industrial regulations themselves.

Finally, we turn to a brief discussion of the possible dynamic consequences of the costs we estimate. We show that, while higher costs are associated with slower growth in employment and productivity in the *registered* manufacturing sector, this association is more muted

[5]Misreporting was a lesser concern in GLV's original setting, as they had access to administrative data. In contrast, the data in the Economic Census are self-reported, which makes the threat of deliberate misreporting more significant in our case.

[6]This is the only way to generate a proportional decrease in the theoretical density, at least in a static model.

[7]This may reflect the fact that the Besley-Burgess measures focus on the IDA, while the regulations we study are entirely different. On the other hand, if the Besley-Burgess measures are meant to capture the general effect of labor laws at the state level, one might expect the two measures to be correlated.

[8]These corruption measures include a subjective, perceptions-based measured of corruption from Transparency International and a measure of the percentage of electricity that is lost in transmission and distribution as reported by the Reserve Bank of India (this latter measure has been used as a proxy for government corruption and ineffectiveness in, for example, Kochhar et al, 2006).

[9]We measure "regulatory dependence" by taking the industry average of the number of inspector visits among Indian firms in the 2005 World Bank Enterprise Surveys.

- or even in the opposite direction - in the *unregistered* manufacturing sector, where the regulations are less salient. This suggests that the costs we estimate may play a role in the "informalization" of the Indian economy, by pushing workers from the formal to the informal sector.

This paper aims to contribute to at least three important strands of literature. The first, which we have already mentioned, is the literature on misallocation of resources and total factor productivity (TFP), as exemplified by Hsieh and Klenow (2009). Our contribution is to provide direct evidence that at least some of the misallocation of resources across firms in India *is* tied to regulations or the enforcement thereof.[10] In particular, we show that size-based regulations (or at least the ways in which they are enforced) lead firms to fall short of their optimal scale, thus distorting the allocation of labor among firms in the economy and, likely, lowering TFP.

Another strand of literature to which we aim to contribute relates to corruption in the enforcement of government policies. Most previous studies (eg: Besley and McLaren (1993); Mookherjee and Png (1995)) have modeled such corruption as collusion between inspectors and firms or citizens: corrupt inspectors allow firms to avoid the de jure costs of abiding by regulations in exchange for bribes. Hence, in these frameworks, corruption *lowers* the costs associated with regulations. However, our results suggest that the costs associated with size-based regulations are *higher* in more corrupt environments, and are thus more in line with an alternative framework in which corruption takes the form of extortion between inspectors and firms (i.e.: corrupt inspectors take advantage of bureacratic regulations in order to extract higher rents from firms in the form of harassment bribes).[11] We present a theoretical model as well as anecdotal evidence from "ipaidabribe.com" to support this interpretation and view the support we provide for this alternative conception of corruption to be another contribution of the paper.

Lastly, this paper is also clearly related to the large literature that more generally investigates the impact of Indian labor regulations on economic outcomes. The literature dates back to at least Fallon and Lucas (1993), but the more recent proliferation seems to be due to the work of Besley and Burgess (2004). In that paper, the authors first interpret state-level amendments to the Industrial Disputes Act (IDA) as either "pro-worker" or "pro-employer" and then aim to show that Indian states that amended the IDA in a "pro-worker" direction experienced slower growth in output, employment, investment and productivity in registered manufacturing. The paper, though extremely influential, has been criticized by Bhattachar-

[10] In future work we hope to determine what portion of the TFP loss from misallocation estimated by Hsieh and Klenow (2009) can be attributed to the regulations we study.

[11] This finding echoes Novosad and Asher (2012), in which it is argued that regulations can provide a means through which politicians can impose costs on businesses.

jea (2006) and Bhattacharjea (2009) on a number of grounds. One of Bhattacharjea's major criticisms is that Besley and Burgess's interpretations of amendments as "pro" or "anti-worker" are subjective and debatable (ie: different people might read and code them in a different way). This criticism affects most of the subsequent academic work on this topic, since most papers use the Besley-Burgess codings, but it is a criticism we are able to sidestep with our methodology. Since our analysis is based only on firm level data and size-thresholds stated explicitly in the laws themselves, it has the advantage of objectivity.

The second contribution we make to this literature is to focus on a set of regulations that have been almost entirely ignored even though they effect a much larger proportion of firms than Chapter VB of the IDA.[12] The only other papers of which we are aware that study regulations that kick in at the 10-worker threshold are Dougherty (2009), Dougherty, Frisancho, and Krishna (2014) and Kanbur and Chatterjee (2013). The latter investigates the Factories Act, which applies to all manufacturing firms that use power and have 10 or more workers (or don't use power and have 20 or more workers), but their focus is to document non-compliance under the act, which we see as complementary to our approach of estimating the costs of the regulations.[13] The papers by Dougherty and co-authors employ state-level indices of labor reforms that differ from the Besley-Burgess codes in that they include consideration of non-IDA regulations such as the Factories Act, but they are constructed from surveys of industry experts and, as such, are by and large subject to similar concerns regarding subjectivity.

Another way in which we distinguish ourselves from the previous literature on Indian regulations is that we explore the effect of regulations in all non-farm segments of the Indian economy - not just in registered manufacturing, on which nearly all previous academic studies have focused. A final contribution of the paper is to provide suggestive evidence that improper government enforcement of regulations may play a role in shifting employment from the registered to the unregistered sector.

In the next section (Section 2), we provide an overview of the relevant institutional details regarding Indian labor and industrial regulations. Section 3 introduces the data and covers some basics about the size distribution of enterprises in India. In Section 4 we go over the theoretical model and our corresponding empirical strategy. Section 5 provides the main results. In Section 6, we interpret the findings, explore the multiple dimensions of variation

[12] Chapter VB of the IDA only applies to manufacturing firms with 100 or more workers. In contrast, the regulations we study affect all firms with 10 or more workers and are thus relevant for a much larger share of firms. We have also tried analyzing Chapter VB of the IDA using the same methodology we employ for the regulations with the 10 worker threshold, but find no effects. I.e.: there does not seem to be a proportional decrease in the density of establishments with more than 100 workers. We also fail to observe "bunching" of firms at sizes just below 100, although the presence of rounding may make such bunching impossible to discern even if it exists.

[13] Our estimated costs are robust to the possibility of noncompliance.

in our results, and investigate the connection between our estimated costed and corruption. Section 7 concludes.

2 Institutional Background: Size-Based Regulations in India

In this paper we attempt to investigate the effects of certain size-based industrial and labor regulations in India. These are regulations that only apply to establishments that exceed a certain size, measured either in terms of a firm's revenue, the amount of fixed capital invested, or the number of workers employed. One of the most significant such thresholds occurs when establishments employ 10 or more workers, after which they must register with the government and meet various workplace safety requirements (under the Factories Act[14], for example), pay social security taxes (under the Employees' State Insurance Act), distribute gratuities (under the Payment of Gratuity Act) and bear a greater administrative burden (under, e.g., the Labor Laws Act).

Not only are the laws numerous, it has been argued that certain components of the laws are antiquated and/or arbitrary. For example we read in the "India Labour Report" that "Rules under the Factories Act, framed in 1948[15], provide for white washing of factories. Distemper won't do. Earthen pots filled with water are required. Water coolers won't suffice. Red-painted buckets filled with sand are required. Fire extinguishers won't do... And so on" TeamLease Services (2006). Firm owners who choose not to comply with such regulations may face costs if discovered and convicted.[16]

In addition to - or in lieu of - the explicit costs of complying with the regulations, establishments with 10 or more workers may be subject to implicit costs associated with increased interaction with labor inspectors, et al, who may have the power to extract bribes and tighten (or ease) the administrative burden firms face. Indeed, inspectors in India have a large amount of discretion regarding the enforcement of administrative law. For example, in some cases, the definition of what constitutes a "day" is at the discretion of the inspector, and it is a commonly held view that "[w]hile grave violations are ignored, minor errors become a scope for harassment" (TeamLease Services (2006)).

This kind of behaviour has been referred to as "harassment bribery" (Basu (2011)). Anecdotal evidence of inspectors using the complexity and sheer amount of paperwork as

[14]Technically the Factories Act applies for 10-plus worker establishments only if they use power. For establishments that do not use power, the Factories Act does not apply until they employ 20 workers.

[15]The Factories Act itself dates to 1948, but the origins of the law go back another 100 years at least, to Britain's first Factory Acts.

[16]These costs may include fines and/or prison sentences.

a way to extract bribes is easy to come by. For example, we have included a selection of citizen reports from "ipaidabribe.com" in Appendix 2, which demonstrate just this kind of behaviour.[17] Interestingly, some of the reports suggest that the size of the bribe paid is a direct linear function of the number of employees - which will be relevant to our estimation procedure later.

As we alluded to earlier, the 10 worker threshold is not the only one relevant; there are other cutoffs at which different regulations become binding. For example, the threshold that seems to have received the most attention, both from academics and the press, is that of 100 workers, at which enterprises in most states become subject to Chapter VB of the Industrial Disputes Act, under which they must be granted government permission to lay off workers. There are other cutoffs still,[18] but in this paper we will focus on estimating some of the costs and effects associated with the regulations that come into force at the 10 worker cutoff. One important limitation of our analysis is that we will not be able to address issues regarding the efficacy of any regulations in promoting worker welfare.

3 Data and the Size Distribution in India

3.1 Data

The data we rely on to investigate the 10-worker threshold comes from the Economic Census (EC) of India. The EC is meant to be a complete enumeration of all (formal *and* informal) non-farm business establishments[19] in India at a given time, *regardless of their size*. It is this last clause that makes the EC different from every other data source available and precisely suited to our needs. Although the 2005 dataset contains a large number of observations (almost 42 million), there is not very detailed information collected on each observation. For each establishment in the data, there is only information on a handful of variables including the total number of workers usually working, the number of non-hired workers (such as family members working alongside the owner), the registration status, the 4-digit NIC industry code, the type of ownership (private, government, etc) and the source of funds

[17]We thank Andrew Foster for this suggestion.

[18]For example, firms with 20 or more workers must abide by the Provident Funds Act. Firms with 50 or more workers must comply with Chapter VA of the Industrial Disputes Act, which requires them to provide compensation and notice to employees prior to lay-offs.

[19]The EC refers to these as "entreprenuerial units" and defines them as any unit "engaged in the production or distribution of goods or services other than for the sole purpose of own consumption." As is common in the literature, we occasionally refer to them as "firms" even though the unit of observation in the data is actually a factory or an establishment, rather than a firm (i.e.: multiple establishments may belong to the same firm). We do this for expositional purposes and justify our use of this convention with the observation that the proportion of establishments that belong to multi-establishment firms is minute.

for the establishment. There is no information on capital, output or profits, and the data is cross-sectional.

The EC has rarely been used in academic papers - possibly because it is cross-sectional, contains a significant amount of measurement error, and only contains information on the handful of variables just enumerated, so that better data sources exist for most purposes. The EC is ideal for our purpose, however, since it includes information on employment size and covers the entire universe of establishments. Other more commonly used datasets, such as the CMIE's Prowess Database, the Annual Survey of Industries (ASI) or the National Sample Survey's (NSS) Unorganized Manufacturing Surveys cover only certain parts of the distribution and thus cannot be used for our purpose. The ASI, for example, only covers factories in the manufacturing sector that have registered with the government under the Factories Act. However, registration under this Act is only required for establishments with 10 or more workers if the unit uses power (20 or more workers if the factory uses no power). Therefore, the selection of the ASI varies discontinuously at precisely the point of interest. Similar limitations on coverage make the other datasets - other than the EC - unsuitable.

Aside from the Economic Census, we also supplement our analysis with data from a variety of other sources. From the ASI we get employment and productivity in the registered manufacturing sector. We generate those same variables for the unregistered sector with data from the Ministry of Statistics and Programme Implementation (MOSPI) and the Reserve Bank of India (RBI). We get data on state and industry level corruption from a) Transparency International's "India Corruption Study 2005", b) the RBI, and c) the World Bank Enterprise Survey for India (2005). Data on State-level regulatory enforcement come from the Indian Labour Year Book.[20] Other measures of state-level regulations come from Aghion et al. (2008) and Dougherty (2009), while industry-level measures of exposure to trade liberalization come from Ahsan and Mitra (2014).

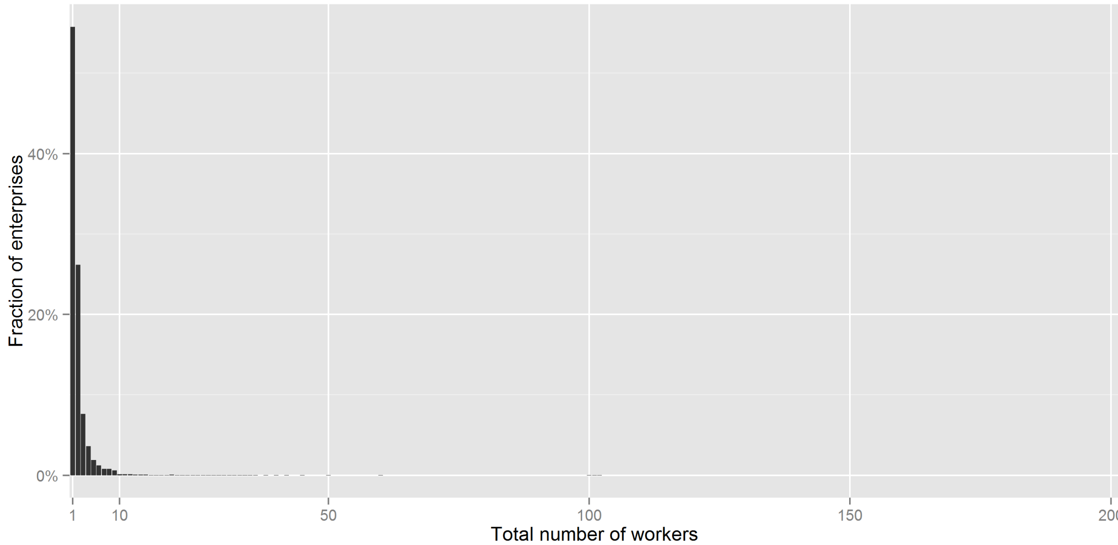
3.2 The Size Distribution of Establishments in India

Figure 1 below shows the distribution of establishments by the number of total workers (hired and non-hired workers) for establishments with up to 200 total workers in 2005. Perhaps the most striking feature of figure 1 is the extraordinary degree to which the distribution is right-skewed. Indeed, about half of all establishments are single person enterprises, while the densities for establishments with 10 or more workers are almost imperceptible.[21] Figure 2 shows the drop in density for establishments with 10 or more workers in detail and figure

[20]We would like to thank Anushree Sinha and Avantika Prabhakar for their considerable and generous help in obtaining these data.

[21]The densities for establishments with more than 200 workers are also imperceptible. We have omitted them only for clarity in the figure.

Figure 1: Distribution of establishment size for establishments with 1-200 total workers, 2005



3 shows the full distribution of establishment size frequencies according to a log scale. Each point represents one bar in the earlier histograms.

Two things are most striking about figure 3. First, the natural log of the density is a linear function of the natural log of the number of total workers. This implies that the unlogged distribution follows an inverse power law in the number of total workers. This pattern will be important for the analysis that follows but it is not very surprising in and of itself: power law distributions in firm sizes have been documented in many countries (e.g. Axtell (2001) and Hernández-Pérez, Angulo-Brown, and Tun (2006)). The second and more unique feature of the distribution is that there appears to be a level shift downward in the log frequency for establishment sizes greater than or equal to 10. Figure 4 shows this effect for establishments with fewer than 100 workers by running an OLS regression of the log density against log firm size and allowing the intercept to vary for firms with 10 or more workers. To the best of our knowledge, ours is the first paper to document this phenomenon in India.

Also of note from the figures above is that there appears to be a significant amount of non-classical measurement error, seemingly due to rounding of establishment sizes to multiples of 5 and 10. The existence of rounding is not surprising given that the data are self-reported and that respondents are asked to give the "number of persons usually working [over the last year]". Partially to alleviate concerns that the non-classical measurement error due to rounding might bias our results (and partially for other reasons to be made explicit shortly), we will employ an estimation procedure which first smooths the data non-parametrically.

Figure 2: Distribution of establishment size for establishments with 5-25 total workers, 2005

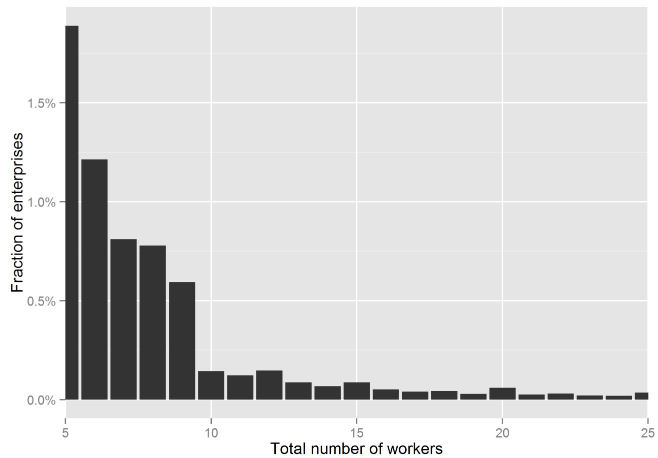
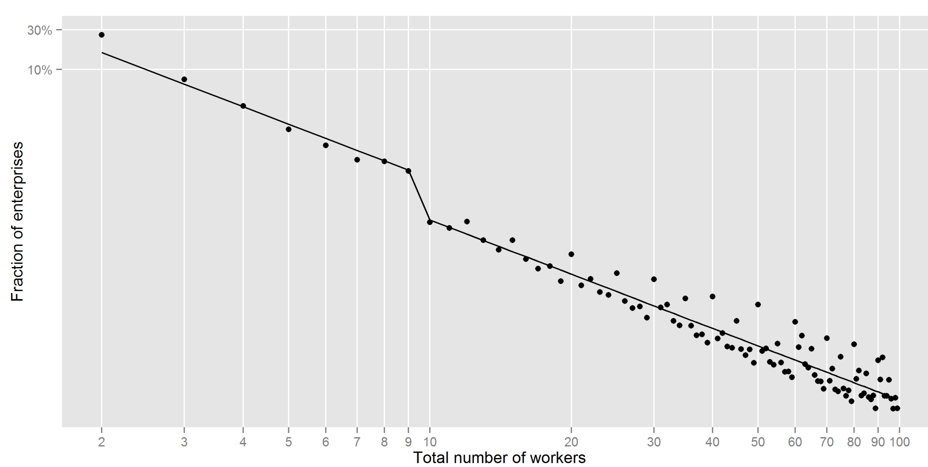


Figure 3: Distribution of establishment size, 2005, log scale

Figure 4: Downward shift at the 10-worker threshold in the distribution of establishment size, 2005, log scale (omitting establishments with more than 100 workers)



4 Model and Empirical Strategy

4.1 Basic Model

To interpret the downward shift from Figure 4 in economic terms, we turn to the model in GLV. In their framework, size-based regulations are assumed to increase the unit labor costs of firms that exceed the size threshold, which results in a downshift in part of the theoretical firm size distribution. From the magnitude of the downshift they observe in the empirical distribution they attempt to estimate the additional labor costs imposed by the regulations.

GLV begin with a distribution of managerial ability ($\alpha \sim \phi(\alpha)$) as the primitive object, following Lucas (1978). As is common in the literature (e.g. Eaton, 2011), they assume that the distribution of managerial ability follows a power law (e.g. $\phi(\alpha) = c_\alpha \alpha^{-\beta_\alpha}$). It is this that will generate a power law in the theoretical firm size distribution. A firm with productivity or managerial ability α faces the following profit-maximization problem:

$$\pi(\alpha) = \max_n \alpha f(n) - w\bar{\tau}n$$

where n is the number of workers a firm employs, $f(n)$ is a production function (with $f'(n) > 0$ and $f''(n) < 0$), w is a constant wage paid to all workers, and $\bar{\tau}$ is a proportional tax on labor that takes the value 1 if $n \leq N$ and τ if $n > N$, where $\tau > 1$.

From the first order condition on this maximization problem, $\alpha = \frac{w\bar{\tau}}{f'(n)}$, one can see that higher productivity establishments/managers will employ more workers, and that firms which cross the threshold (N) and must therefore pay higher labor costs will hire fewer workers than they would otherwise. This latter feature is built to match the observed "downshift" in the actual firm size distribution to the right of the regulatory threshold.

One can informally characterize the solution as follows: one set of managers with particularly low productivity (below some threshold α_1) will be effectively unconstrained. These managers would have chosen to hire fewer than 10 workers whether or not the regulation was present. Another set of managers with slightly higher productivity (between some thresholds α_1 and α_2) would, in the absence of the regulation, have chosen to hire 10 or more workers - but who, in the presence of the regulation, obtain higher profits by hiring only 9 workers to avoid the discontinuous increase in costs implied by crossing the threshold. These mangers should be "bunched up" at 9. The last set of managers are those with high enough productivity ($\alpha > \alpha_2$) that it is not worth it to avoid the regulation and so they choose to exceed the threshold and pay the tax. However, these managers face higher marginal costs than they would in the absence of the regulation and therefore employ fewer workers by a constant proportion (resulting in a "downshift" in the logged firm size distribution).

An exact expression for the distribution of firm size, $\chi(n)$, can be recovered as a transformation of the distribution of managerial ability, $\phi(\alpha)$, since the first-order conditions on the firms' maximization problems imply a monotonic relationship between α and n. The key result is that a function of the tax enters multiplicatively in the expression for the density of firms size n (for all $n > 9$). Therefore, the function of the tax enters additively in the *log density* for all firms large enough to be subject to the tax.

Formally, the density of firms with n total workers, $\chi(n)$ is given by:

$$\chi(n) = \begin{cases} \left(\frac{1-\theta}{\theta}\right)^{1-\beta}(\beta-1)n^{-\beta} & if \quad n \in [n_{\min}, N) \\ \left(\frac{1-\theta}{\theta}\right)^{1-\beta}\left(N^{1-\beta} - \tau^{-\frac{\beta-1}{1-\theta}} n_u^{1-\beta}\right) & if \quad n = N \\ 0 & if \quad n \in (N, n_u) \\ \left(\frac{1-\theta}{\theta}\right)^{1-\beta}(\beta-1)\tau^{-\frac{\beta-1}{1-\theta}} n^{-\beta} & if \quad n \geq n_u \end{cases}$$

where θ measures the degree of diminishing returns to scale, capturing both features of the production function and market power, β represents the negative slope of the power law and τ is the implicit per worker tax. Taking logs and combining the first and last cases[22] leads to:

$$\log(\chi(n)) = \log\left[\left(\frac{1-\theta}{\theta}\right)^{1-\beta}(\beta-1)\right] - \beta\log(n) + \log(\tau^{-\frac{\beta-1}{1-\theta}})1\{n > 9\}$$

This leads to an estimating equation:

$$\log(\chi(n)) = \alpha - \beta\log(n) + \delta 1\{n > 9\} \tag{1}$$

We can identify τ according to:

$$\tau = \exp(\delta)^{-\frac{1-\theta}{\beta-1}}$$

τ is thus a function of θ, β and δ. We get estimates for α, β and δ from equation 1. Knowing α and β pins down θ, which allows us to identify τ.

4.2 Concerns Regarding Misreporting

Before proceeding further, we must consider how our results might be affected by the possibility of misreporting. This is important because one of the underlying assumptions of the analysis above is that the size distribution of firms as observed in the Economic Census is accurate. However, since the data are self-reported, it is possible that plant managers may misreport information to Economic Census enumerators. Specifically, if the managers are aware of the increased regulatory burden that is associated with employing 10 or more

[22] In other words, we ignore the bunching at N and the valley directly after, since these are features that are not easily observable in the data. Instead we focus on the ranges $n \in [n_{\min}, N)$ and $n > n_u$.

workers, and if they believe that the EC enumerators will relay information to government regulatory bodies, they may wish to hide the fact that their actual employment exceeds the threshold. To see how this type of behavior might affect our results, we model it explicitly in the following subsection.

A further reason to be concerned about the possibility of misreporting is due to the fact that Economic Census enumerators were required to fill out an extra form containing the address of any establishment that reported 10 or more workers. It is conceivable that enumerators might have found it preferable to under-report the number of workers for establishments with 10 or more workers in order to avoid the extra burden of filling in the "Address Slip". Although we do not model this type of problem explicitly in what follows, the implications are nearly identical to those of the model we do explicitly analyze.[23]

4.3 A Theoretical Model of Misreporting

Our model of misreporting starts with the theoretical model from Section 4.1, and amends it to allow firms to choose not only their true employment (n), but also their *reported* employment (l). Then, a firm with productivity α faces the following profit-maximization problem:

$$\pi(\alpha) = \max_{n,l} \alpha f(n) - wn - \tau l * 1(l > 9) - F(n,l) * p(n,l)$$

where $\alpha, f(n), w$ and τ are all defined as they were previously. The problem is identical except that now firms pay the extra marginal cost, τ, only on their *reported* employment, and not on their true employment. Furthermore, they only pay this cost if their reported employment exceeds the threshold.[24] There is now an incentive for firms to misreport their employment in a downward direction (i.e.: to set $l < n$). Counteracting this incentive is that misreporting firms may be caught by the authorities with probability $p(n,l)$, and made subject to a fine, $F(n,l)$. As written above, both the probability of being caught and the magnitude of the fine may in general depend on n and l in an arbitrary way. However, if one is willing to make the assumption that the expected cost of misreporting ($F * p$) is an increasing and convex function of the degree of misreporting, $n - l$, it will be possible to use an estimation technique that will be only minimally biased by the presence of misreporting. Fortunately, based on our understanding of the context in which firms make these decisions,[25]

[23]The only difference is that higher fixed costs would replace higher marginal costs. It is, moreover, easy to show that if our estimation strategy is robust to the model of misreporting we do analyze, it is also robust to this second type of misreporting as well.

[24]In point of fact it is most likely that firms' answers to Economic Census enumerators have no impact on their regulatory burden, but it is possible that firms believe otherwise, and that is what is relevant.

[25]This understanding is informed by informal interviews with small businesses in Chennai and our reading

we believe that this is the most reasonable assumption on the functional form of the expected cost that one could make.

One plausible way to obtain convex misreporting costs is to suppose that firms are caught with a probability that is linearly increasing in the degree of their misreporting (i.e.: $n - l$) and subject to a fine if caught which is also a linear function of their misreporting. Another possibility is that the probability of being caught is itself an increasing and convex function of the degree of misreporting and the fine if caught is fixed. In what follows we will assume the latter for clarity of exposition, but the analysis is identical for any assumption that yields convex costs of misreporting.

Specifically, suppose that misreporting firms are caught with probability $p(n,l) = \frac{(n-l)^2}{100}$, and pay a fixed fine, F, if caught. Then their profit maximization problem is:

$$\pi(\alpha) = \max_{n,l} \alpha f(n) - wn - \tau l * 1(l > 9) - F * \frac{(n-l)^2}{100}$$

The solution to this problem can be informally characterized as follows. The lowest productivity firms (those with α below some threshold, α_1) will be unconstrained, choosing $n \leq 9$ and reporting truthfully ($l = n$). Higher productivity firms, with $\alpha \in [\alpha_1, \alpha_2]$, will choose $n > 9$, exceeding the regulatory threshold, but will find it profitable to misreport their employment, setting $l = 9$. These firms will only *appear* to be "bunched" up at 9, but will in fact have higher employment. The last category of firms are those with $\alpha > \alpha_2$, which are productive enough to warrant hiring work forces so large that they cannot avoid detection with reasonable probability and must report $l > 9$. Even these firms, however, with both $n > 9$ and $l > 9$ do not find it profit-maximizing to report truthfully. They can save on their unit labor costs by shading their reported employment, and will choose $l = n - \frac{50}{F}\tau$. Note that the degree of misreporting is by a constant amount, rather than a constant proportion.[26]

More formally, the log of the density of firms with true employment n, $log\chi(n)$, is given by:

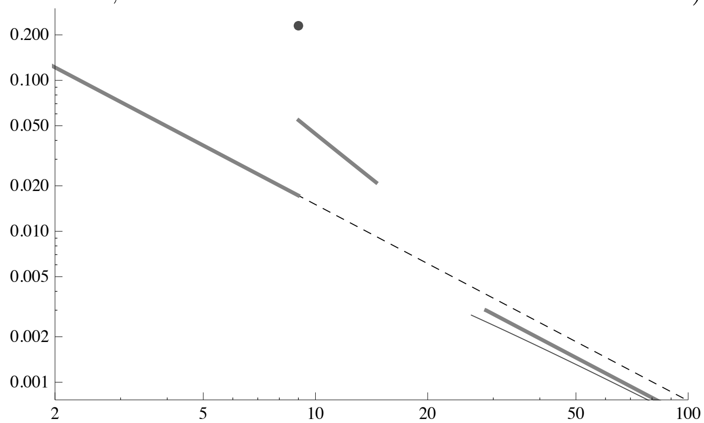
$$log\chi(n) = \begin{cases} logA - \beta log(n) & if \quad n \in [n_{\min}, 9) \\ log[\xi(n)] & if \quad n \in [9, n_m(\alpha_2)] \\ 0 & if \quad n \in (n_m(\alpha_2), n_t(\alpha_2)) \\ logA'(\tau) - \beta log(n) & if \quad n \geq n_t(\alpha_2) \end{cases}$$

while the log of the density of firms with reported employment l, $log\psi(l)$ is given by:

of the secondary literature.

[26]This outcome is a result of the convex cost assumption.

Figure 5: Theoretical Model of Misreporting, log scale (thick line = true distribution; thin line = reported distribution; dashed line = counterfactual distribution)



$$
log\psi(l) = \begin{cases} logA - \beta log(l) & if \quad l \in [l_{\min}, 9) \\ log(\delta_l) & if \quad l = 9 \\ 0 & if \quad n \in (9, l_t(\alpha_2)) \\ logA'(\tau) - \beta log(l + \frac{50}{F}\tau) & if \quad l \geq l_t(\alpha_2) \end{cases}
$$

where terms have been simplified and collected.[27] Both of these densities are graphically represented in Figure 5 under specific values of the parameters (the true distribution, $\chi(n)$, is represented by a thick line, and the reported distribution, $\psi(l)$, is in blue). The key things to note are the following. First, for the range $l \leq 9$, the true distribution coincides with the reported/observed distribution. Second, there appears to be bunching at 9 in the reported distribution, but these firms in fact have greater than 9 workers. Third, compared to the distribution for $n < 9$, the true distribution *and the reported distribution* for $n \gg 10$ are downshifted ($A'(\tau) < A$), just as was the case in the model without misreporting.[28] Fourth - and most significantly - the reported distribution converges to the true distribution for large l: $\lim_{l \to \infty} \beta log(l + \frac{50}{F}\tau) - \beta log(l) \to 0$. This is due to the fact that the misreporting is by a constant amount (as noted earlier), rather than by a constant proportion.

To conclude this subsection on the theoretical implications of allowing for misreporting, we make two observations. First, misreporting may lead us to observe "bunching" in the firm size distribution when in reality there may be none. This is irrelevant for us since our estimation strategy does not rely on the bunching in any way. Second, misreporting may lead the reported/observed distribution to understate the true distribution *close to the cutoff*. However, because the reported distribution converges to the true distribution for large l/n, misreporting is not able to induce a downshift in the reported distribution that

[27]Derivation to be added in an appendix.

[28]As before, the downshift is a function of τ.

differs from the downshift in the true distribution at large values of l. Therefore, if we use an estimation strategy that focuses mostly on values far from the cutoff, our estimate of the downshift using the observed distribution is likely to reflect the real downshift and thus we are likely to avoid this source of bias. We develop such an estimation strategy in the following subsection.

Before proceeding, however, we should note again that the above analysis assumes that the expected costs of misreporting are strictly convex. There exist non-convex functional forms of the cost function which may lead one to observe a downshift in the reported distribution that is greater than the one in the true distribution, thus biasing any estimates of τ upwards.

4.4 An Empirical Strategy Robust to the Possibility of Misreporting

Since convex misreporting costs imply that misreporting will only distort the distribution of reported establishment size versus the true distribution of establishment size close to the cutoff, we estimate the model on the *full* distribution of establishment size. Since estimating equation 1 treats each establishment size as one observation, using the full distribution of establishment size will mean that the model is primarily estimated using data far from the 10-worker cutoff.[29] However, estimating equation 1 on the full distribution of establishment size introduces two complications. First, we cannot perform the estimation on the empirical PMF for large firm sizes, since the empirical probability mass is truncated at the reciprocal of the number of observations (see figure 6 below), while the underlying density continues to diminish in establishment size. Second, respondents appear to round their reported number of workers to the nearest multiple of 5 (see figure 2), a phenomenon that is more pronounced for larger establishments and that could bias our results.

To address these two problems, we first estimate the density associated with each number of workers $\chi(n)$ non-parametrically using the method of Markovitch and Krieger (2000), which addresses the econometric issues arising in nonparametric density estimation of heavy-tailed data. We then use the nonparametric density estimates as a basis for fitting the model in equation 1, augmented by dummy variables for having 1, 2, 8, 9 and 10 - 20 workers.[30]

[29] The largest establishment in the 2005 EC has 22,901 workers.

[30] The rationale for flexibly modeling the density at 1 and 2 workers is that own account enterprises and 2-worker enterprises are likely to be household enterprises and may therefore differ fundamentally in character from their larger counterparts. The rationale for flexibly modeling the density at 8 and 9 workers is that the theory above predicts that the reported density just below the cutoff will be biased upwards by any misreporting effects. Similarly, the theory also predicts that values above - but close to - the threshold may also be biased (downwards). Therefore we also flexibly control for such values (10 to 20) as well, although doing so has only a very small effect on the estimates: as explained above, the estimates are driven mostly

Figure 6: Downward shift at the 10-worker threshold in the distribution of establishment size estimated on nonparametric density estimates, 2005, log scale (including all establishments). Black points = actual data; Grey = smoothed data.

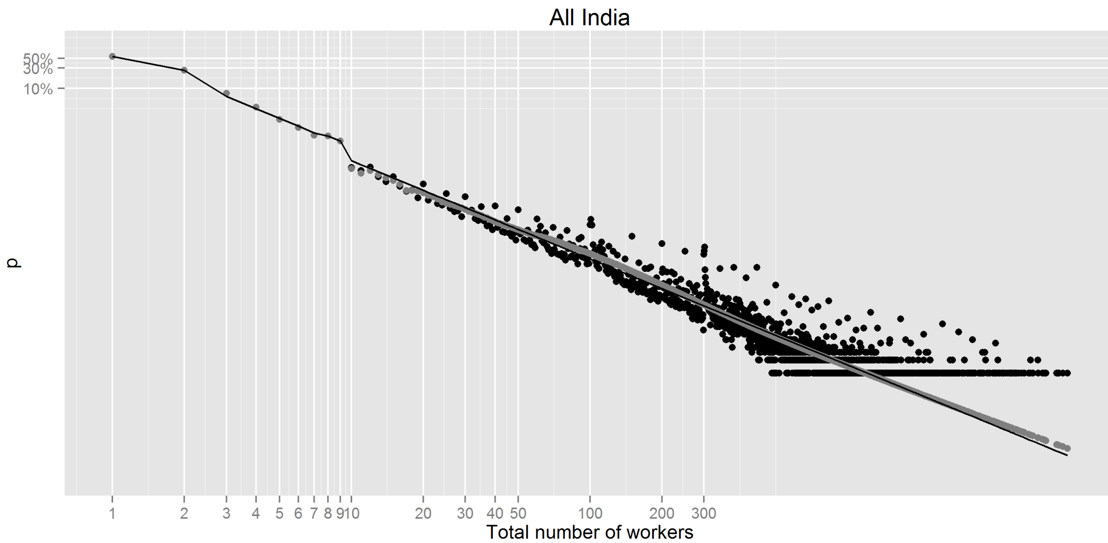


Figure 6 depicts the strategy. The black dots show the raw data. The grey dots represent the result of the first step: nonparametric density estimates associated with each establishment size. The line shows the fit of the model in equation 1, augmented by the dummy variables, to the nonparametric density estimates.

Figure 6 above provides some evidence for the model described in section 4.3. The observed establishment size distribution appears to converge back to a power law with the same slope as for establishments with fewer than 10 workers, but deviates slightly from that slope at sizes just above the 10-worker cutoff. In the next section we report the results of the estimation.

5 Preliminary Results

In this section we apply the estimation procedure described above to the 2005 Economic Census of India and report the results. Standard errors obtained from a wild cluster bootstrap procedure with 200 replications are given in parentheses.[31] In the tables below, we first report estimates for $\tau - 1$ at the All-India level and for a selection of States, Industries and Ownership Types. Estimates for *all* States, Industries and Ownership Types are reported in the Appendix. The All-India estimate on $\tau - 1$ is .35 and is statistically significant. This

by observations relatively far from the threshold.

[31] We cluster at the firm size level to allow for the possibility that reporting errors may be correlated by firm size.

means that, on average, establishments in India that hire more than 9 workers act as though they must pay additional labor costs of 35% of the wage per additional worker. In the tables and figures it can be seen that there is substantial variation in the magnitude of our estimates of the per-worker tax by State, Industry and Ownership Type. For example, the point estimate on $\tau - 1$ for the State of Kerala is .14, while the estimate for Bihar, on the other hand, is .70, implying that establishments in Bihar act as though they must pay a tax of 70% of the wage for each additional worker they hire past 9 workers.

We also observe substantial differences in the size of τ by industry: it appears that the effective tax is highest for establishments in construction and retail. As one might expect, the tax is nonexistent for establishments in the public administration sector (in fact it is negative, but this seems to result from the fact that the assumed power law does not fit the distribution of establishments in this sector well). Similarly, when looking at the differences by ownership type, we find that the estimates for τ are highest for private firms (especially unincorporated proprietorships), and nonexistent (or negative) for government-owned firms, where presumably the regulatory burden is less than in the private sector.

Estimates of τ by State Using the Full Distribution of Establishment Size

Level	$\tau - 1$
All-India	
	.347
	(0.059)
By State	
Bihar	.693
	(0.069)
Gujarat	0.165
	(0.047)
Kerala	0.138
	(0.033)
Uttar Pradesh	0.502
	(0.069)
By Industry	
Construction	.478
	(0.047)

Manufacturing	.268
	(0.039)
Wholesale, retail	.637
	(0.115)
Public admin., social security	-.311
	(0.031)
By Ownership Type	
Government and PSU	-.092
	(0.028)
Unincorporated Proprietary	.490
	(0.005)

6 Discussion and Investigation of Mechanisms

6.1 Interpretation of Results

Thus far we have argued that the observed downshift in the distribution of establishments with 10 or more workers is related to the existence of certain labor and industrial regulations that become binding at that point. But if the regulations are responsible for the observed effect, then differences in the substance or application of the regulations should explain (at least part of) the great variation we observe across States and Industries.[32] In this section we explore these dimensions of variation with the goal of reaching a deeper understanding regarding the causes and consequences of the costs we have tried to estimate. The regressions we do are cross-sectional and the variables used are endogenous, so the results cannot be given a causal interpretation, but we find them instructive nevertheless.

To preview our results, we do observe a correlation between our estimated costs (τ) and certain measures of the substance of the regulations. Moreover, we also find a robust and independent correlation between our estimated costs and several different measures of

[32]The variation across ownership types is straightforward to explain: the regulations are clearly not applied in the same way to privately owned enterprises and government enterprises. An additional explanation is that government establishments are not profit maximizing and thus would require a different motivational theory altogether to produce the observed power law distribution.

corruption/poor state governance, suggesting that it is not only the regulations themselves but also their enforcement and application that is responsible for the high costs we estimate. We also sketch a theoretical framework of bribery and extortion which casts light on the proper interpretation of our empirical results. Finally, we present some suggestive evidence that our costs may have significant negative dynamic implications, as they are associated with *lower* growth *in* employment and productivity in registered manufacturing - and *higher* growth in employment in unregistered manufacturing.

6.2 τ and Corruption: Evidence from the Interstate Variation

We start by regressing our state-level estimates of τ against other established measures of the regulatory environment (see Table 2).[33] These measures include the "Besley Burgess" (BB) measure of labor regulations from Aghion et al. (2008) and several measures from Dougherty (2009). The first is a measure of the number of amendments that a state government has made to the Industrial Disputes Act in either a "pro-worker" or "pro-employer" direction, as interpreted by Aghion et al. (2008), who update the measure to include amendments up to 1997.[34] Positive values indicate more "pro-worker" amendments, which are assumed to imply a more restrictive environment for firms operating in those states. Dougherty (2009) also provides state level measures that reflect "the extent to which procedural or administrative changes have reduced transaction costs in relation to labor issues" Dougherty et al. (2014). Higher values therefore indicate an improved environment for firms. Dougherty's measures are unique in that they cover a wide range of labor-related issues - not just the IDA. In the analysis below, we will focus on measures from Dougherty (2009) that cover reforms regarding 1) the Factories Act and 2) an overall measure of reforms. All relevant variables in our analysis have been rescaled to have mean zero and standard deviation one, with the goal of allowing comparability between regression coefficients in different specifications.

In Table 2, correlations are reported between τ and the three measures both by themselves and while controlling for other factors (notably state GDP per capita and the state's share of employment in manufacturing). The Besley Burgess (BB) measure does not seem to be correlated with τ (although our power is limited by the very small number of observations) while the two measures from Dougherty (2009) are significantly correlated after applying controls (though not all the correlations are strongly significant) and have the "correct" sign: states that saw more "transaction cost reducing" reforms have lower τs. [35] On the one

[33]Note that the estimates of τ we use in all the analysis below were generated using the procedure in Section 4.4 that we have argued is robust to possible misreporting and non-classical measurement error.

[34]Since there have been few state-level amendments to the IDA between 1997 and 2005, this measure should be largely the same in 2005.

[35]In this and most of the analysis ahead, we focus on the 18 largest Indian States, for which data are most

hand the lack of correlation between τ and the BB measure is not surprising, as the latter capture variation only due to state amendments to the Industrial Disputes Act, which does not vary over the ten person threshold. On the other hand, if the Besley Burgess measure is meant to capture the general regulatory environment (which is how it is used in countless studies), we might well expect it to correlate with our measure of regulatory costs. That the correlation does not hold may therefore be of interest.

While the prediction regarding the correlation between τ and BB_97 may be ambiguous, that is not the case for Dougherty's measures of transaction-cost reducing reforms related to the Factories Act. We should expect our measure of τ to correlate negatively with the latter, since the Factories Act does vary across the 10 worker threshold, and indeed we see that it does. τ is also correlated with Dougherty's more comprehensive measure of reforms, one which aggregates reforms across all areas, although it does not appear to correlate with any other subcomponents (which are not depicted here).

Table 2: Tau vs Other Measures of Regulations

	(1) tau	(2) tau	(3) tau	(4) tau	(5) tau	(6) tau	(7) tau	(8) tau	(9) tau
Besley-Burgess measure (regs)	-0.0734 (0.204)	-0.00841 (0.192)	0.0481 (0.172)						
Dougherty measure (all reforms)				-0.289 (0.201)	-0.407** (0.174)	-0.408* (0.198)			
Dougherty measure (FA reforms)							-0.211 (0.187)	-0.318* (0.166)	-0.304 (0.181)
log of net state domestic product pc		-0.432* (0.226)	-0.592** (0.214)		-0.604** (0.206)	-0.575** (0.241)		-0.590** (0.217)	-0.605** (0.257)
share of employment in manufacturing		-3.490 (4.886)	2.657 (5.090)		3.899 (3.281)	2.962 (4.934)		3.486 (3.435)	4.215 (5.163)
share of privately owned establishments			-11.66 (6.768)			2.003 (5.895)			0.529 (6.221)
share of registered establishments			3.042* (1.530)			-0.0440 (1.476)			0.654 (1.469)
Constant	0.641*** (0.204)	5.315** (2.165)	15.79** (6.707)	0.653*** (0.187)	6.207*** (1.962)	4.259 (6.113)	0.631*** (0.189)	6.091** (2.068)	5.481 (6.517)
Observations	15	15	15	18	18	18	18	18	18

* p¡0.10, ** p¡0.05, *** p¡0.01, Standard errors in parentheses
Only including Major Indian States

In addition to the above measures regarding state-level changes to the statutory, proce-

consistently available and which offer the most precise estimates of τ (the power law relationship breaks down in smaller states when there are not enough observations).

dural and administrative aspects of the regulations, we also regress τ against certain other measures of the labor environment. Table 3 reports the results of τ regressed against per capita measures of strikes, man-days lost to strikes, lockouts and man-days lost to lockouts. One might imagine that strikes and lockouts capture relevant features of the regulatory and labor environment,[36] but we do not find them to be robustly correlated with τ.

One might also expect τ to be correlated with aspects of the regulatory enforcement. To test this hypothesis we regress τ against state level variables related to enforcement such as the number of inspections, convictions, and fines levied under various regulations.[37] The results of the regressions for a subset of the enforcement related variables are shown in Table 4. In short, the only enforcement variable that is even close to being significantly correlated with τ is the percentage of factories registered under the Factories Act that have been inspected. However, as can be seen from the table, the enforcement data are only available for a small subset of the major states, leaving very little power in the regressions. Furthermore, the regressions shown exclude Uttar Pradesh, which is a substantial outlier in the enforcement data.

[36] For example, some industrial regulations explicitly undermine or support the rights of parties to engage in strikes or lockouts.

[37] These data were obtained from the 2005 Indian Labour Yearbook, which we were able to attain with the generous help of Anushree Sinha and Avantika Prabhakar of NCAER.

Table 3: Tau vs Strikes and Lockouts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	tau	tau	tau	tau	tau	tau	tau	tau
strikes per capita	-0.272*	-0.196						
	(0.145)	(0.148)						
mandays lost due to strikes per capita			-0.119	-0.148				
			(0.157)	(0.159)				
lockouts per capita					-0.0544	-0.0915		
					(0.146)	(0.143)		
mandays lost due to lockouts per capita							-0.0527	-0.0995
							(0.145)	(0.139)
log of net state domestic product pc		-0.400		-0.493*		-0.506**		-0.515**
		(0.234)		(0.238)		(0.235)		(0.235)
share of employment in manufacturing		2.548		4.482		3.831		3.754
		(3.644)		(4.171)		(3.995)		(3.913)
Constant	0.721***	4.352*	0.646***	5.017**	0.620***	5.191**	0.618***	5.291**
	(0.187)	(2.204)	(0.212)	(2.272)	(0.198)	(2.221)	(0.197)	(2.222)
Observations	18	18	17	17	18	18	18	18

Standard errors in parentheses

Only including Major Indian States

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Tau vs Enforcement of Regulations

	(1) tau	(2) tau	(3) tau	(4) tau	(5) tau	(6) tau	(7) tau	(8) tau
percent of factories inspected	0.448*							
	(0.230)							
convictions under FA per factory		-0.0914						
		(0.411)						
prosecutions under SEA per capita			-0.122					
			(0.357)					
fines under SEA per capita				0.323				
				(0.342)				
prosecutions per inspection					-0.134			
					(0.254)			
fines per inspection under SEA						2.598		
						(3.557)		
cases disposed per inspection under SEA							-9.616	
							(16.45)	
cases disposed per cases prosecuted under SEA								1.058
								(1.094)
log of net state domestic product pc	-0.0180	-0.648	-1.545**	-2.220**	-1.572**	-1.977**	-1.471**	-1.610**
	(0.921)	(1.265)	(0.606)	(0.783)	(0.537)	(0.677)	(0.600)	(0.500)
share of employment in manufacturing	-2.361	4.091	4.873	5.550	4.525	7.130	4.486	2.514
	(7.120)	(12.61)	(4.855)	(4.542)	(4.883)	(5.277)	(4.848)	(5.340)
Constant	0.970	6.706	15.42**	22.20**	15.72**	20.08**	12.60	16.57***
	(8.791)	(11.88)	(5.835)	(7.767)	(5.150)	(6.986)	(8.218)	(4.802)
Observations	10	9	13	13	13	13	13	13

Standard errors in parentheses

Only including Major Indian States (except UP) for which data exist.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To briefly summarize the results so far, when regressing τ against regulatory substance, enforcement or industrial disputes, one only observes correlations for certain specific types of measures of those phenomena. In contrast, in our remaining analysis, we will demonstrate that our measures of τ are strongly and robustly correlated with corruption, almost regardless of how it is measured. Table 5 reports the results of regressing τ against corruption as measured in a 2005 Transparency International (TI) Survey.[38] Column 1 includes all states for which there is data, while the remaining columns include only the 18 largest Indian states. Column 3 adds controls for state GDP per capita, share of manufacturing

[38]The TI corruption measure is based on a survey of perceptions and experience regarding corruption in the public sector.

in employment and some others, while Column 4 adds the aggregate measure of regulatory reform from Dougherty (2009). With no exceptions, the coefficient on the TI corruption score is consistently significant and very large in magnitude: a one standard deviation increase in a state's corruption score is associated with a .5 standard deviation increase in τ. In particular, the fact that the coefficient remains significant in Column 4 even after controlling for Dougherty's measure of regulatory reforms suggests that the relationship between τ and corruption is at least partly independent from the relationship with the regulations themselves.

In what follows we will use the TI corruption score as our primary measure of corruption. One might be concerned, however, that the TI measure may be flawed as it is the result of individuals' perceptions (it has been argued by some that the perception of corruption is an unreliable indicator for actual corruption). Therefore, we also regress τ against an alternative measure of corruption that is not perception based to check for robustness of the relationship between τ and corruption: Table 6 reports the results of τ regressed against the percent of a state's available electricity that was lost in transmission and distribution in 2005. This variable has been used by other researchers as a proxy for corruption and poor state governance, and has the virtue of being a concrete and objective measure that does not depend on perceptions Kochhar, Kumar, Rajan, Subramanian, and Tokatlidis (2006). As with the TI Corruption Score, the correlations between τ and this alternative measure of corruption are significant and large in magnitude regardless of sample or controls - including, again, the addition of the Dougherty measure of regulatory reform in Column 4. To make sure that the results are not driven by the actual transmission of electricity, we control for per capita electricity available in Column 5 - which does not affect the results.

Table 5: Tau vs Transparency International Corruption Score

	(1)	(2)	(3)	(4)
	tau	tau	tau	tau
TI Corruption Score	0.422**	0.583***	0.574***	0.512***
	(0.157)	(0.145)	(0.153)	(0.139)
log of net state domestic product pc			-0.381*	-0.446**
			(0.191)	(0.172)
share of employment in manufacturing			7.362*	6.444*
			(4.007)	(3.569)
share of privately owned establishments			-2.662	-2.057
			(4.805)	(4.258)
share of registered establishments			1.455	0.665
			(1.106)	(1.048)
Dougherty measure (all reforms)				-0.296*
				(0.142)
Constant	0.557***	0.644***	5.494	5.976
	(0.153)	(0.138)	(4.847)	(4.291)
Observations	20	18	18	18
States Included	All	Major	Major	Major

* p¡0.10, ** p¡0.05, *** p¡0.01, Standard errors in parentheses

Table 6: Tau vs Transmission and Distribution Losses

	(1) tau	(2) tau	(3) tau	(4) tau	(5) tau
electricity	0.318*	0.648**	0.663**	0.566**	0.708**
transmission and distribution losses	(0.165)	(0.244)	(0.253)	(0.237)	(0.268)
log of net state			-0.477*	-0.536**	-0.459*
domestic product pc			(0.222)	(0.205)	(0.229)
share of employment			7.651	6.515	6.817
in manufacturing			(4.812)	(4.439)	(5.094)
share of privately			-2.148	-1.440	-1.980
owned establishments			(5.677)	(5.200)	(5.824)
share of registered			1.513	0.644	1.577
establishments			(1.307)	(1.284)	(1.343)
Dougherty measure				-0.317*	
(all reforms)				(0.172)	
Electricity					0.119
available (GWH)					(0.182)
Constant	-8.42e-09	0.643***	5.936	6.322	5.610
	(0.163)	(0.163)	(5.746)	(5.253)	(5.910)
Observations	35	18	18	18	18
States Included	All	Major	Major	Major	Major

* p¡0.10, ** p¡0.05, *** p¡0.01, Standard errors in parentheses

Although the state-level correlations between τ and corruption appear to be robust, the regressions lack exogenous variation and are subject to the concern that our measures of corruption may be correlated with omitted variables that are also correlated with τ. To partially address these concerns, we attempt to take advantage of State X Industry level heterogeneity. In particular, inspired by Novosad and Asher (2012), we use 2005 World Bank Enterprise Survey (WBES) data to create an industry-level measure of "dependence on government bureaucracy". Specifically, Indian firms in the 2005 WBES were asked how many times in a year they had an inspection or other required meeting with a government official. Averaging the firm-level responses by industry, we classify industries according to their average number of visits with officials (i.e., their dependence on government bureaucracy). If some industries have more meetings with officials, and if corruption takes place during some of these meetings, we would imagine that the costs of corruption would be highest for firms in those industries with the highest dependence on bureaucracy *and* in those states that have the highest levels of corruption. That is, we would expect that the *interaction* between industry level dependence on bureaucracy and state level corruption is positive. If found to be the case, it would be harder to argue that the result is due to the presence of omitted variables.

The hypothesis is tested in Table 7. To do so we generate our measures of τ at the State X Industry level[39] and interact each of our state level measures of corruption with a) the industry average number of visits from officials and b) the industry average duration of visits from officials. We include the interaction with average *duration* of visits as a placebo test: it is not clear that the duration of an inspection should be positively or negatively correlated with corruption.[40] We then regress our State X Industry measures of τ against the covariates including interaction terms. Our prior is that the interaction of corruption with duration of visits should be less significant than the interaction with number of visits. Indeed, this is mostly what we observe. The interaction between our measures of corruption and the number of visits is at least weakly significant (at the 10% level) for one of the two measures, while the interaction between corruption and average duration of visits is never significant.

To summarize our results from these investigations, we find:

1. a correlation between τ and certain aspects of the substance of regulations as measured in Dougherty (2009),
2. a nonexistent or inconclusive relationship between τ and measures of the labor environment and enforcement of regulations, and
3. a strong and robust relationship between τ and two distinct measures of corruption.

Although none of these results can be said to be causal, we find them suggestive of a relationship between corruption and high labor costs. Next, we turn our attention to the question of how and why greater corruption would lead to higher labor costs for firms. To this end, in the following subsection we outline a simple theoretical framework to elucidate the potential connection.

[39] Industries here are categorized according to their groupings in the World Bank Enterprise Surveys, which distinguishes 24 distinct industry categories. Examples include “auto components”, “leather and leather products”, and “food processing”.

[40] In particular, corruption may lead to longer inspections if the process of extracting the bribe takes time, or it may lead to shorter inspections if corruption obviates the need to carry out the actual inspection.

Table 7: Tau vs State Level Corruption Interacted with Industry Level "Dependence on Regulation" (with Industry FEs)

	(1)	(2)	(3)	(4)
	tau	tau	tau	tau
2005 TI	0.132*	0.140*		
Corruption Score	(0.0668)	(0.0666)		
electricity			0.0583	0.0493
transmission and distribution losses			(0.114)	(0.110)
number of	0.127		0.130	
inspections	(0.0829)		(0.0945)	
duration of		-0.00610		-0.109
inspections		(0.124)		(0.143)
corruption score	0.101*			
X num inspections	(0.0545)			
corruption score		0.0513		
X duration of inspections		(0.0691)		
electricity TDLs			0.0112	
X num of inspections			(0.0848)	
electricity TDLs				-0.0698
X duration of inspections				(0.107)
log of Net State	-0.185***	-0.185***	-0.197***	-0.194***
Domestic Product pc	(0.0364)	(0.0374)	(0.0428)	(0.0427)
Constant	-0.244	0.0235	-0.235	-0.217
	(0.187)	(0.442)	(0.187)	(0.498)
Observations	189	189	189	189

* p¡0.10, ** p¡0.05, *** p¡0.01, Standard errors clustered at the State Level, Industry FEs included.

6.2.1 A Theoretical Framework for Understanding Corruption Between Inspectors and Firms

We find it helpful to distinguish between two types of corruption that could take place between inspectors and firms: collusion and extortion. Collusion takes place when inspectors allow firms to avoid the costs of complying with regulations in exchange for bribes. However, poor state governance (which here would imply an inability to control corruption) would then lead to *lower* costs for firms, as greater corruption would make it easier to avoid the full costs of regulation.[41] However, what we observed in Section 6.2 was a robust *positive* correlation between effective costs (τ) and poor governance/corruption. To explain this phenomenon, we need a model of *extortion*. In this section, we will sketch the intuition for such a model. A fuller (but still simple) model of extortion and bribery is provided in Appendix 3.

Let us start with the observation that all firms reporting at least 10 employees fall under the jurisdiction of certain regulations. Imagine, now, that the regulations are so complex so as to make it impossible (or prohibitively costly) for any firm to be fully in compliance with all aspects of the law as written.[42] Then, an inspector can, at any time, choose to subject a firm under his jurisdiction to a penalty e, which may include financial (e.g.: fines) and/or non-financial elements (e.g.: harassment, time needed to defend claims of violations, etc). We can think of the extent of the penalty (e) as a function of state governance: properly functioning governments hire and motivate inspectors to pursue substantive violations rather than minor ones, while inspectors in corrupt or dysfunctional governments can get away with threatening to impose high penalties for even minor technical violations if a bribe is not paid (i.e.: extortion).

In such an environment, firms reporting 10 or more employees (and hence under the jurisdiction of the inspector) may face a choice between exposing themselves to the penalty, e, or paying a bribe, b. Assume that inspectors face no costs or benefits from imposing the penalty on the firm, but naturally benefit from receiving the bribe. There is thus a surplus to be had from paying/receiving the bribe b and avoiding the penalty. If the inspector and firm Nash Bargain over the surplus with bargaining weights α and β, respectively, the problem is the following:

$$\underset{b}{max} \ (b)^{\alpha}(e-b)^{\beta}$$

The solution is for the firm to pay a bribe $b = \frac{\alpha}{\alpha+\beta} * e$. The cost born by the firm is therefore increasing in α, the bargaining weight of the inspector, and in e, the maximum penalty to which the firm can be subjected. It is reasonable to imagine that this maximum level of extortion, e, is roughly proportional to the size of the firm, so that $e = e' * n$, where n is the number of workers in the firm and e' is the per worker level of extortion. In that case the bribe per worker, $\frac{b}{n}$, is equal to $\frac{\alpha}{\alpha+\beta} * e'$.[43]

[41] See, for example, a model of corruption such as the one in Khan, Khwaja, and Olken (2014).

[42] This does not not require much imagination. As we mentioned in Section 2, many of the laws have components that are antiquated, arbitrary, contradictory and confusing. That the laws may be impossible to fully comply with is suggested by some of the anecdotes we provide in Appendix 2 as well as the following observation, which we re-quote: "Rules under the Factories Act, framed in 1948, provide for white washing of factories. Distemper won't do. Earthen pots filled with water are required. Water coolers won't suffice. Red-painted buckets filled with sand are required. Fire extinguishers won't do... And so on" (TeamLease Services, 2006).

[43] Again, we provide some support for the claim that bribes are proportional to the number of workers

This framework can be embedded into the firm's choice of true and reported employment as modeled in Section 4.3. In particular, the firm now faces a choice between reporting employment greater than or less than 10, where reporting less than 10 allows it to avoid the costs of bribery, and reporting greater than 10 exposes it to the bribery costs. In that framework, τ corresponds to $\frac{b}{n}$, and is therefore increasing in the bargaining power of the inspector (α) and the corruption level of the state (e'). In this way, we can make sense of the empirical results above in terms of this basic framework. Again, a more fully fleshed out model that explicitly incorporates features missing here (such as an appeals process and inspector types) is provided in Appendix 3.

6.3 Possible Consequences of τ

In the subsections above, we tried to argue that our estimated costs (τ) are most likely due, not only to the substance of the regulations themselves, but also to high levels of corruption. In this subsection we will indicate possible consequences of high values of τ. Again, the results cannot be given a causal interpretation, but we find them compelling nevertheless. In what follows we use two distinct measures of τ: one which is created using all the enterprises in a state, regardless of economic sector (τ) and another which is created using only the enterprises engaged in manufacturing (τ_{manuf}).

Table 8 displays the results of employment growth in the manufacturing sector between 2010 and 2005 at the State Level regressed against our two measures of labor market distortions (τ and τ_{manuf}) as well competing measures (BB and Dougherty). For each of the four measures, we observe its performance as a predictor of future employment growth in *registered* manufacturing as well as its correlation with employment growth in *unregistered* manufacturing. Interestingly, in the regressions of employment growth in registered manufacturing against τ and τ_{manuf}, the coefficient on τ is negative and at least weakly significant, while the coefficient for employment growth in unregistered manufacturing is positive - significantly so in the case of τ_{manuf}. This result makes sense: we should expect higher costs to negatively effect the sectors to which the costs apply - in this case the registered sector, since that is under the ambit of labor regulations while the unregistered sector is not. If these correlations reflect a causal chain, it would mean that high levels of regulator costs and corruption (as measured by τ) are pushing employment from the registered to the unregistered sector.

Also included in Table 8 are the results of employment growth in manufacturing regressed against the BB and Dougherty measures. Neither regressor has a coefficient that

with anecdotal evidence from ipaidabribe.com in Appendix 2.

is statistically significant or of a meaningful magnitude.[44] Putting aside the considerable caveat that none of these results has the virtue of exogenous variation, it would appear to be the case that our measures of labor market distortions do a better job of predicting future employment growth (or the lack thereof) than the established alternatives. This is also true when considering future growth in manufacturing *productivity* rather than employment, as shown in Table 9. Higher levels of τ are associated with slower growth of productivity in the *registered* manufacturing sector (less so in the unregistered sector)

Table 8: Manufacturing Employment Growth (2005 - 2010) vs Tau and Other Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	reg manuf	unreg manuf	reg manuf	unreg manuf	reg manuf	unreg manuf	reg manuf	unreg manuf
tau	-0.0240	0.00197						
	(0.0176)	(0.0233)						
tau (manuf)			-0.0471**	0.0623**				
			(0.0217)	(0.0256)				
Besley-Burgess measure (regs)					-0.00525	0.00979		
					(0.00731)	(0.0142)		
Dougherty measure (all reforms)							0.0226	-0.0143
							(0.0130)	(0.0159)
log of net state domestic product pc	0.00312	0.0189	0.0107	0.0192	0.00413	0.0140	0.0212	0.0136
	(0.0178)	(0.0214)	(0.0145)	(0.0161)	(0.00863)	(0.0168)	(0.0154)	(0.0195)
share of employment in manufacturing	-0.393	0.00558	-0.708**	0.435	0.0194	-0.559	-0.515*	0.0525
	(0.258)	(0.329)	(0.258)	(0.325)	(0.186)	(0.362)	(0.245)	(0.323)
Constant	0.0969	-0.182	0.0372	-0.229	0.0209	-0.0675	-0.0861	-0.131
	(0.173)	(0.209)	(0.139)	(0.152)	(0.0825)	(0.160)	(0.147)	(0.182)
Observations	18	17	18	17	15	15	18	17

* p¡0.10, ** p¡0.05, *** p¡0.01, Standard errors in parentheses, Only including Major Indian States

[44] One might argue that it is not quite fair to regress growth between 2010 and 2005 on a regressor that uses data only up until 1997 (as is the case for the BB measure). However, a) we have duplicated these results using from growth from 1997 to 2002 and the results are the same, and b) the Besley Burgess measure from Aghion et al. (2008) should be largely the same in 2005 due to the lack of state level reforms between 1997 and 2005.

Table 9: Manufacturing Productivity Growth (2005 - 2010) vs Tau and Other Measures

	(1) reg manuf	(2) unreg manuf	(3) reg manuf	(4) unreg manuf	(5) reg manuf	(6) unreg manuf	(7) reg manuf	(8) unreg manuf
tau	-0.0321**	0.00522						
	(0.0146)	(0.0239)						
tau (manuf)			-0.0512**	-0.0567*				
			(0.0181)	(0.0275)				
Besley-Burgess measure (regs)					-0.00266	-0.00372		
					(0.0122)	(0.0154)		
Dougherty measure (all reforms)							0.0167	0.00973
							(0.0122)	(0.0166)
log of net state domestic product pc	-0.0160	-0.00902	-0.00478	-0.0120	-0.00455	-0.00723	0.00438	-0.00793
	(0.0148)	(0.0220)	(0.0121)	(0.0174)	(0.0143)	(0.0182)	(0.0145)	(0.0204)
share of employment in manufacturing	0.206	0.0392	-0.154	-0.349	0.453	0.526	0.0728	0.0104
	(0.214)	(0.338)	(0.215)	(0.350)	(0.310)	(0.392)	(0.230)	(0.338)
Constant	0.141	0.124	0.0454	0.198	-0.0208	0.0530	-0.0678	0.119
	(0.144)	(0.214)	(0.116)	(0.163)	(0.137)	(0.174)	(0.138)	(0.190)
Observations	18	17	18	17	15	15	18	17

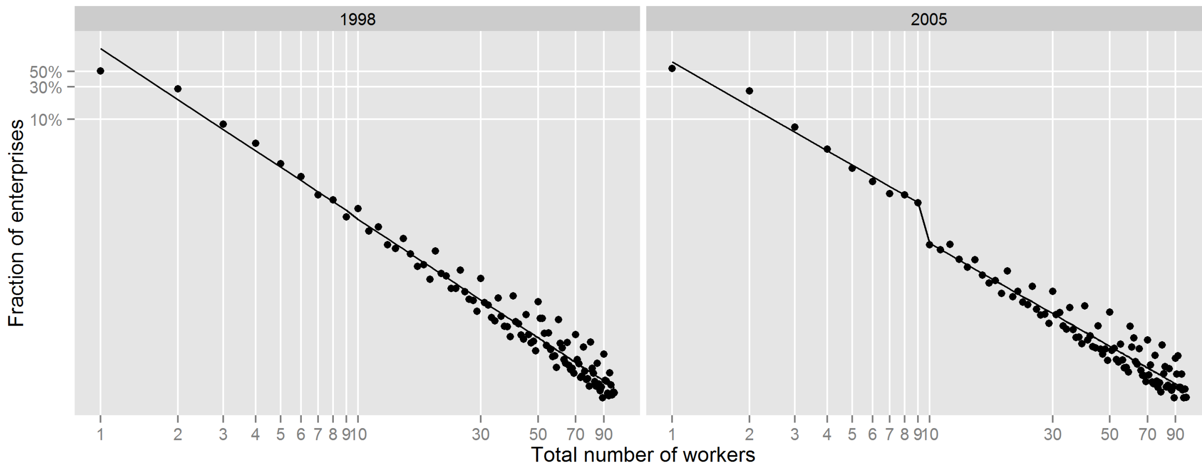
* p¡0.10, ** p¡0.05, *** p¡0.01, Standard errors in parentheses, Only including Major Indian States

6.4 Inter-temporal Variation: A Final Puzzle

As we have noted, all of the analysis above uses data only from the 2005 Economic Census. However, the discontinuity observed in the 2005 data does not appear in the 1990 or 1998 ECs. Explaining the puzzling inter-temporal variation is a main goal of our future work. Perhaps the simplest explanation is that the data quality of the EC improved between 1998 and 2005. Indeed, it is intuitive that the presence of a downshift will be harder to discern upon the introduction of measurement error. This explanation has received anecdotal support from our meetings with the Directors of the state Directorates of Economics and Statistics, who largely claimed to be more confident in the results of the 2005 EC than in the results of previous rounds. One reason for this could be that the 2005 EC was the first wave in which ICR ("intelligent character recognition") was used to read in the raw data. This technology should have gone a long way in alleviating the considerable amount of error that comes from manual interpretation and typing.

But one might also be concerned in the other direction: that somehow the distortion observed in 2005 is anomalous and is perhaps due to something like a change in the EC's enumeration practices. Based on our interviews with officials and enumerators in charge of collecting these data, however, we believe this is unlikely. While we have discovered that enumeration practices have changed slightly over the years, we have not discovered changes that could have produced the specific patterns we observe. For example, unlike the previous

Figure 7: Variation in the distribution of establishment size across time:



waves, the 2005 Economic Census included an "address slip" that was meant to be filled out for establishments with 10 or more workers. It is conceivable that enumerators, in an effort to avoid the extra work of filling out the address slip, preferred to misrepresent the number of workers for establishments with more than 10 workers. However, while this could reasonably explain why there are fewer 10, 11 and 12 person establishments, we find it hard to understand how this kind of phenomenon could explain why there are also fewer 30, 40 and 50 person establishments (see section 4.3 for more on this). Furthermore, in post-enumeration checks done in West Bengal, Bihar and Tamil Nadu, this kind of misrepresentation was not found to be in occurrence.

Nor does the culprit seem to be changes in the regulations themselves. Indeed, none of the regulations which we assume are responsible for the discontinuity in 2005 were greatly changed *in the right direction* between 1990 and 2005. There were reforms on the margin (reflected in the Dougherty (2009) measures), and these do seem to be correlated with our measures of τ, but most of the changes have gone in the direction of loosening regulations and thus cannot explain why τ would have increased over time. Enforcement has also changed to some degree, but we have not yet found evidence that it can explain the variation in our data (see the interstate analysis above).

Another possible (but ultimately unlikely) explanation is that changes in the competitive environment, particularly related to the increased exposure to international markets and competition, are responsible. The period in question (1998 to 2005) saw heavy reductions in protective barriers from foreign competition - particularly through the elimination of non-tariff barriers. However, in our preliminary analysis (not yet reported) we do not find a strong link between trade liberalization and τ, and such link as exists goes in the opposite direction.

A final possibility is that changes in the availability of contract labor cause the discontinuity to show up in 2005. Indeed, there was a large speed-up in the use of contract labor over the period,[45] however state-level changes in the fraction of contract labor in registered manufacturing are not robustly correlated with τ. The absence of such a correlation is not necessarily evidence that such a link does not exist, but it does not give support to the hypothesis either.

We have been able to share this intertemporal paradox with a number of experts regarding these issues in India but have not yet been able to find a watertight explanation. This continues to be a priority in our ongoing work.

7 Conclusion

Our goals in this paper are 1) to document the effect of size-based labor regulations on the misallocation of resources across firms via the employment decisions of business enterprises, 2) to estimate the net costs of the set of regulations that become binding when establishments choose to employ 10 or more workers, and 3) to shed some light on the source of these costs by demonstrating that corruption in the form of harassment bribery may play a large role in making Indian regulations costly. To the best of our knowledge, this paper is the first to provide cost estimates of regulations in India (particularly non-IDA regulations), the first to analyze the effects of regulations without using necessarily subjective evaluations of state-level amendments to labor laws, and the first to provide evidence for the link between regulatory costs and corruption.

To accomplish these tasks, we use the 2005 Economic Census of India, an uncommonly used dataset which is uniquely suited to our task because it includes the entire universe of non-farm enterprises. In our investigation, we find a significant level shift down in the natural log of the probability mass of establishments with 10 or more workers. Adapting a method from Garicano et al. (2013), we interpret this as evidence of substantial per-worker costs of operating above the 10 worker threshold. At the all-India level, we find that operating at or above the 10-worker threshold is associated with a 35% increase in the unit cost of labor as modeled. Furthermore, we observe a great deal of variation in our estimated costs by state, industry and ownership type. We estimate the highest (lowest) costs for privately owned firms (government-owned firms) and firms in construction (public administration and defense).

Exploring this variation reveals that Indian states with the highest costs also have the

[45] In the registered manufacturing sector, the share of contract labor in total labor increased from 15% to 26%. Prior to this period, its growth was markedly slower.

highest levels of corruption and poor governance (as measured through two distinct indices), and that firms in industries with high bureaucratic dependence are exposed to particularly high costs if they are also in highly corrupt states. This analysis suggests that the size of regulatory costs may have as much to do with how regulations are implemented and who implements them, as with the content of the specific labor and industrial laws themselves. We hope that these findings will help shift the present debate away from arguments over the pro or anti-labor stance of regulations and towards arguments about clarity, bureaucracy and the proper enforcement of regulations.

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Appendix 1: Full Results by State and Industry[46]

Table 10: Estimates of Tau by State

State	*Tau*	*Standard Error*
Andhra Pradesh	-.159	.038
Assam	.322	.041
Bihar	.693	.069
Delhi	.427	.048
Gujarat	.165	.047
Himachal Pradesh	-.165	.023
Haryana	.007	.044
Jharkhand	.388	.061
Karnataka	.52	.06
Kerala	.138	.033
Maharashtra	.332	.038
Madhya Pradesh	.379	.047
Orissa	.283	.044
Punjab	.096	.041
Rajasthan	.32	.05
Tamil Nadu	.397	.059
Uttar Pradesh	.502	.069
West Bengal	.151	.054

[46]Standard errors generated using a wild cluster bootsrap procedure with 200 replications.

Table 11: Estimates of Tau by Industry

Industry	*Tau*	*Standard Error*
Mining and quarrying	-.042	.047
Manufacturing	.268	.039
Electricity, gas and water supply	-.367	.022
Construction	.478	.047
Wholesale and retail trade	.637	.115
Hotels and restaurants	.468	.06
Transport, storage and communications	.334	.056
Financial intermediation	-.105	.044
Real estate, renting and business activities	.601	.062
Public administration and defence	-.311	.031
Education	-.173	.042
Health and social work	.076	.03
Other service activities	.264	.057
Extraterritorial organizations and bodies	.024	1.315

Table 12: Estimates of Tau by Owernship Type

Ownership Type	*Tau*	*Standard Error*
Government and public sector undertaking	-.092	.028
Non profit institution	-.04	.038
Unincorporated proprietary	.43	.087
Unincorporated partnership	-.058	.028
Corporate non financial	-.197	.026
Corporate financial	-.18	.023
Co-operative	-.007	.022

Appendix 2: Anecdotal Evidence Regarding Harassment Bribery from "ipaidabribe.com"

"I am a small factory owner in Kirti Nagar Industrial Area. We follow almost all rules laid down by government for the welfare of workers. Now, even if we follow everything there is always somethings where we lack and which needs improvement. We have a factory inspector by the name of Mr.R.B.Singh (M: 9818829355). He comes to all the factories in our area, inspects them, find mistakes and then harass and blackmails us. According to him he can get our factories sealed. To avoid this, to save our time and to save the unnecessary paperwork we pay him every year. I have paid him twice in two years i.e. 10000 & 15000 and this is common with all factories. Please take a strict action against him so that he learns a lesson. I am sure he is not alone. All his colleagues are equally corrupt."

(Reported on August 11, 2014 from New Delhi, Delhi — Report #131791)

"During the routine labor verification process by the labor department at our office, we were advised by the consultant to pay the labor inspector a bribe to ensure that they don't keep calling us for needless paperwork."

(Reported on June 28, 2011 from Chennai, Tamil Nadu — Report #35064)

"The Labour Department requires a dozen odd registers to be maintained some of them which are totally outdated and pointless. E.g: Salary register, Attendance register, Leave register etc.

Our IT office has an electronic system that logs all entries/exits and leave taken. We have the records and offerred to provide it to them in a printout.

Salaries are paid electronically via bank transfer.

The officer declined and said it must be maintained in a manual register!

Finally an arrangement was made where we maintain a few records manually and the rest he would overlook.

Cost of arrangement Rs 1500 twice a year even if the officer shows up only once a year for the inspection!

He is supposed to inspect twice so expects to be paid even for the time he did not show up!" (Reported on October 13, 2010 from Chennai, Tamil Nadu — Report #44950)

"Well i had gone to renew my labour license and after all the running around in the bank and the department, the signing authority asked me to pay Rs.500 for signing. When asked why 500, i was told since there are 5 employess for Rs.100 each." (Reported on December 31, 2010 from Hyderabad, Andhra Pradesh — Report #43509)

"... in my third visit i met one of office peon in Labour office he guided me for the bribe he also investigated and *advised me for bribe according to the number of Employees deployed on contract basis* and for this valueble suggestion he charged me Rs. 100. Again with full confidence i went to the ALCs desk and straight away i offered him the packet which was contains the amount of Bribe Rs. 3000/- ... He issued me the license after office hours..." (Reported on March 30, 2011 from Mumbai, Maharashtra — Report #39133)

"Applying for shop & establishment [registration] & procured all documents relating to the registration. Finally inspectors are asking Rs.1000 as a bribe. If any other notice received by the company for resolving that another Rs.2000 and above , it depends on the company" (Reported on March 28, 2014 from Bangalore, Karnataka — Report #99016)

"Officer name Naveen Kumar . Mobile no. 9468104694- He is asking for a bribe of 60,000 and is saying will issue a negative report under labour laws." (Reported on January 24, 2014 from Gurgaon, Haryana — Report #83365)

Appendix 3: Modeling Extortion (ie: Harassment Bribery)

In this Appendix we model size-based regulations in an environment where corrupt inspectors use the fact that de jure regulations are numerous, complex and burdensome in order to extort bribes from firms (ie: harassment bribery). The model aims to illustrate how corruption may lead to higher per worker costs for firms that exceed the 10 worker threshold, while being as parsimonious as possible. The set-up and timeline is described below and in Figure 8.

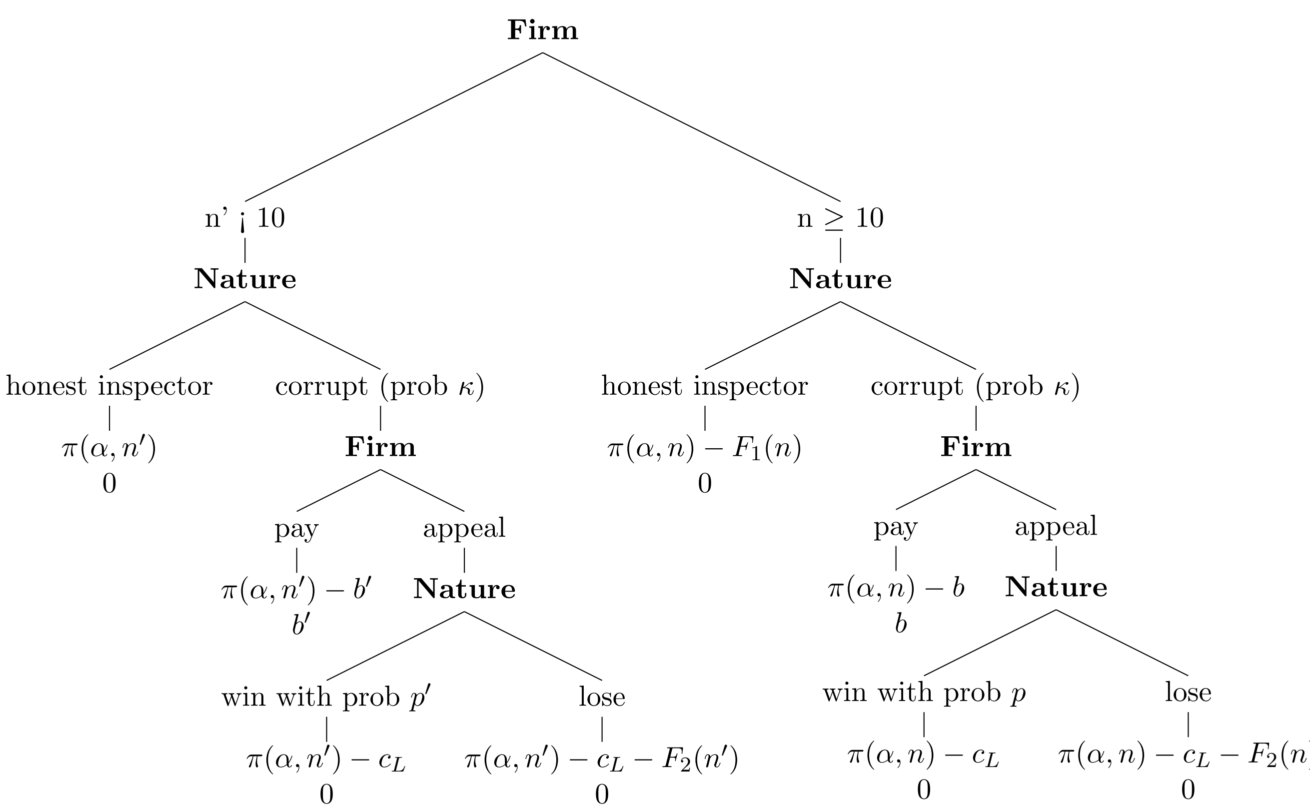
First, firms must choose their number of workers ($n \geq 10$ or $n' < 10$).[47] As in Section 4.1, firms are characterized by a productivity parameter α, so that firms with higher productivity would like to choose higher n. If firms choose n greater than or equal to 10, they come under the legal purview of size-based regulations, which makes it more difficult for them to appeal extortionary practices on the part of inspectors. After choosing a level of employment, firms are randomly matched with an inspector. With probability κ, the inspector is corrupt; otherwise the inspector is honest. An honest inspector will enforce a reasonable interpretation of the spirit of the regulations if the firm has more than 10 workers. To be compliant with this "reasonable" interpretation of the regulations will cost the firm an amount $F_1(n)$, which may in general depend on the number of workers in the firm. A firm with fewer than 10 workers incurs no regulatory costs if matched with an honest inspector.

If the firm is instead matched with a corrupt inspector, the inspector will threaten to report the firm for technical infractions unless it pays a bribe (which we denote b or b', depending on whether the firm has chosen $n \geq 10$ or $n' < 10$), the value of which is

[47] Throughout, primes will denote the values of variables on the side of the decision tree in which firms hire less than 10 workers.

determined by Nash Bargaining. The firm may choose to pay the bribe or appeal the threatened fine in court. If appealing the fine in court, the firm will win with probability p (or p') but will incur legal fees (c_L) with certainty. If it wins the case, the firm has no further financial obligations. If the firm loses, it is obliged to pay an amount $F_2(n)$, which we take to be much larger than $F_1(n)$. This last assumption is tantamount to supposing that a reasonable level of compliance with regulations is not extremely costly in comparison to the punishments that could be brought by an inspector for violating the regulations - which may be a reasonable assumption in contexts where inspectors have a great amount of bargaining power and/or punishments can involve prison sentences. The assumption is also necessary for the framework to be one of extortion rather than collusion: if $F_1(n)$ were large in comparison with $F_2(n)$, firms would benefit from collusion and would face lower costs with corrupt inspectors than with honest ones. It is also plausible that both $F_2(n)$ and $F_1(n)$ are increasing functions of the number of workers, especially if we acknowledge that the full cost of any fine would include the opportunity cost of a manager's time. We will consider the case where the total fines are directly proportional to the number of workers: $F_i(n) = f_i * n$. The decision tree representing the firm's choices described above is provided in Figure 8.

Figure 8: Decision Tree



An important assumption is that p', the probability of a firm's winning the case when $n' < 10$, is much higher than p, the probability of winning the case when $n \geq 10$. The idea is that a firm with less than 10 workers is not under the legal purview of the regulations, so any case regarding regulatory infractions brought against the firm would have no standing in court. In what follows, we will take $p = 0$ and $p' = 1$ for simplicity. As previously mentioned, if the firm meets a corrupt inspector, the value of the bribe paid to avoid going to court is determined through a process of Nash Bargaining over the surplus, where α and β are the bargaining weights of the inspector and firm, respectively:

$$\underset{b}{max} \;\; (b)^{\alpha}(c_L + (1-p)F_2(n) - b)^{\beta}$$

The solution of this maximization problem is that $b = \frac{\alpha(c_L+(1-p)F_2(n))}{\alpha+\beta}$ (and $b' = \frac{\alpha(c_L+(1-p')F_2(n))}{\alpha+\beta}$, for firms with less than 10 workers). Given that firms meet corrupt inspectors (and thus pay bribes) with probability κ and meet honest inspectors (and thus pay $F_1(n)$) with probability $1-\kappa$, the expected cost for a firm with greater than 10 workers is $\kappa b + (1-\kappa)F_1(n)$, while the expected cost for a firm with less than 10 workers is $\kappa b'$. Taking the difference and substituting in our expressions for b and b', we get that firms that cross the 10 worker threshold face an increase in expected costs of $\kappa\frac{\alpha}{\alpha+\beta}(p'-p)F_2(n) + (1-\kappa)F_1(n)$.

We are interested, however, in the increase in *per worker* costs that firms face when exceeding the 10 worker threshold, not the increase in total costs (as discussed earlier, an increase in per worker costs is the only way to produce a downshift in the logged firm size distribution in a static model). Thus, we divide the last result by the number of workers, n, to get per worker costs. Before doing so, we make the further simplifications that $p = 0$, $p' = 1$, α and β both equal 1 (equal bargaining weights), and that all fines are proportional to firm size ($F_i(n) = f_i * n$). Then, the increase in per worker costs for firms that exceed the 10 worker threshold is $\kappa\frac{f_2}{2} + (1-\kappa)f_1$.

From the last result we see that if $f_2 \gg f_1$ (in particular, in this case, if $f_2 > 2f_1$), then the increase in a firm's per worker costs for exceeding the 10 worker threshold (i.e.: what we call τ in the paper) is increasing in the proportion of corrupt inspectors, κ. Again, that we are considering a context of extortion or "harassment bribery" is implied by the assumption $f_2 \gg f_1$. It is this condition (that f_2 is very large) that gives corrupt inspectors the power to extract heavy bribes. We think it is a reasonable assumption given the anecdotal evidence regarding bribery we have found (some of which we present in Appendix 2). To conclude, the model above illustrates conditions that may explain the correlations we observed between corruption and τ in Section 6. In particular, the conclusion of the model is that firms in states with a higher proportion of corrupt inspectors (ie: more corrupt states), face higher per worker costs for exceeding the 10 worker threshold (higher τ).