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Beyond Political Connections

A Measurement Model Approach to Estimating Firm-level Political Influence in 41 Economies

David C. Francis
Robert Kubinec

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Abstract

This paper considers the political influence of private firms. While such influence is frequently discussed, there is limited analysis of how firms combine political interactions, and under what conditions, to gain influence. The exception is the large literature on firms with political connections, with findings generally showing large gains to firms with those direct relationships. This paper extends the discussion of influence beyond political connections alone and uses a rich firm-level data set from 41 economies, which includes information on several interactions with political actors. Using a Bayesian item response theory (IRT) measurement model, an index of Political Influence is estimated, with the prior assumption that political connections yield more influence. Membership in a business association is found to enhance influence, while such influence is offset by bribes, state ownership, firm size, and a reliance on collective lobbying. Political Influence is found to be broadly higher in economies with poorer governance but more dispersed in those with better governance. Within economies, higher influence is associated with a higher likelihood of reporting a small number of competitors, higher sales, and lower labor inputs relative to sales. These findings are robust across several models that incorporate high-dimensional fixed effects, incorporating measurement error in the index, and varying these relationships over several governance measures.

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Beyond Political Connections: A Measurement Model Approach to Estimating Firm-level Political Influence in 41 Economies

David C. Francis*
World Bank

Robert Kubinec †
New York University Abu Dhabi

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*Senior Economist, World Bank, dfrancis@worldbank.org

†Assistant Professor of Political Science, Division of Social Sciences, New York University Abu Dhabi, rmk7@nyu.edu

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1 Introduction

All over the world, firms exert political influence. While this influence varies in its intensity, form, and effectiveness, it is widely understood to be in competition with the interests of other firms, groups, and the public at large, whether those interests are complementary or adversarial (Becker, 1983). Some of the ways in which firms try to manifest this influence are well established and tested in the economics and political science literature. In particular, the leverage of a connection to political leadership has drawn substantial attention, with most analyses showing large gains to well-connected firms (Fisman, 2001; Faccio, 2006; Malesky and Taussig, 2009; Earle and Gehlbach, 2015). Such connections are not the only means available to firms to exert influence, of course. Firms have many possible interactions with political decision-makers, and each presents a chance for firms to seek gains, but also they give political actors the ability to extract rents from those firms (Shleifer and Vishny, 1994; Harstad and Svensson, 2011; Bertrand et al., 2018; Haber et al., 2003; Markus, 2015; Frye, 2017). That is, while political connections may result in influence, that influence may be dampened or enhanced by particular combinations of political interactions, including through legal channels, such as business associations, or through generally illegal ones, like bribery. Just the same, firms can certainly realize influence without having a political connection. In this paper, we provide an original measure of firm-level political influence for 41 economies, increasing our knowledge about how a diverse array of state-business interactions affect firm performance.

Political influence is a social construct, and so it cannot be directly observed; as such, we treat political influence as a latent concept. This paper uses an original, firm-level data set from 41 diverse economies (mainly in Europe, Central Asia, the Middle East, and North Africa) to understand how firms engage in interactions with public officials to gain influence. To do so, we draw upon data on several interactions between public officials and private firms. We do not start with a prior assumption of which interactions increase political influence, other than through political connections themselves, which we treat as indicative of influence. We use a Bayesian latent variable model, a form of item response theory (IRT), which allows for the aggregation of several indicators of firm political activity along with reported political connections as the reference category. By linking observed combinations of political interactions to the latent concept of influence—and several underlying predictors—we not only show how political connections interact with other engagements between firms and political decision-makers, but we also reveal how certain interactions may complement or temper the influence of those connections. The result is an index, estimated with error, of firm-level Political Influence, which aggregates diverse state-business relationships into a theoretically relevant measure.[1]

In Section 2, we lay out a broad framework for understanding how firms may combine their interactions with public officials to garner political influence: we note that drawing political influence through these interactions carries a transactional cost and that the resulting influence is in competition with other

[1]To clarify for readers, we generally capitalize the estimated measure of Political Influence, as opposed to the underlying concept of influence.

interests, including competing firms. This leads us to set up our IRT measurement model, dealing with the underlying data described in Section 3. Reported in Section 4, we find that while political influence is supported by connections—an assumption of our model—as well as participation in business associations, influence is dampened by the extraction of bribes, larger firm size, state ownership, and finding industry lobbying useful. Put differently, greater Political Influence provides a means to stave off the associated costs of bribes, state ownership, greater size, and a reliance on lobbying. Using several measures of governance quality, we find that average Political Influence tends to be higher in economies with poorer governance. By contrast, better governance is generally associated with a broader *dispersion* of influence within an economy. Within an economy, as well, we find that greater Political Influence is associated with a higher likelihood that firms face a low number of competitors, and that they report a higher level of sales and lower labor input intensity relative to those sales. We also report these results varying over governance quality and report findings that largely support our transaction cost framework. Section 5 concludes.

2 Political Influence and Its Measurement

2.1 The Measurement Problem

Political influence is the ability of an actor, such as a firm, to obtain beneficial regulatory decisions (defined broadly) from bureaucrats and policy makers. No actor, though, will be able to exert influence perfectly, and so political interests will be in competition. To illustrate this, we begin with Becker (1983)'s model of political competition. The full derivation of the model is contained in Becker (1983), with further elaborations in Becker (1985) and Becker and Mulligan (2003); for our purposes a few key concepts are important. First, we consider two groups, which are on net subsidized, s, and taxed, t. The total amount of taxes transferred is equal to the number of members in that group n_t multiplied by the average tax $\bar{t}$ within a cumulative function that allows for deadweight losses, $F(\bar{t})$. The mirror image of this is the total amount of subsidies transferred, which is given by $n_s G(\bar{s})$. This gives a larger budget constraint so that:

$$n_t F(\bar{t}) = n_s G(\bar{s}) \quad (1)$$

Each group maintains an influence function, $\Theta_{g=s,t}$, which is a function of the pressure exerted by both groups, p_s and p_t, as well as other factors x. The respective influence of each group is also a function of its relative size, expressed as $\frac{n_s}{n_t}$. The influence functions are defined to equal the respective sides of Eq. 1, with the understanding that the influence of the taxed group Θ_t attempts to lower taxes and so is negative. This results in:

$$-\Theta_t(p_t, p_s, \frac{n_s}{n_t}, x) \equiv n_t F(\bar{t}) = n_s G(\bar{s}) \equiv \Theta_s(p_t, p_s, \frac{n_s}{n_t}, x) \quad (2)$$

That is, on the whole, influence is zero sum, and the relative pressure of each group (for given values of influence) is inversely related to the other group, scaled by the relative amounts of deadweight loss in $F(.)$ and $G(.)$.

Political pressure carries a cost, m_g (with the average cost by group being $\bar{m}_g$), and in equilibrium, each group will continue to apply pressure until the marginal change in pressure relative to the marginal increase in this cost ($\frac{\partial p_g}{\partial m_g}$) equals the marginal change in utility (U_g') relative to the change in the average cost of exerting that pressure m_g, as shown in Becker (1985)[2]:

$$U_s' = \Theta_s(\frac{\partial p_s}{\partial m_s}) \tag{3}$$

$$U_t' = \Theta_t(\frac{\partial p_t}{\partial m_t}) \tag{4}$$

Where $U_s' \equiv -\frac{\partial U_s}{\partial \bar{m}_s} / \frac{\partial U_s}{\partial \bar{s}}$ and $U_t' \equiv -\frac{\partial U_t}{\partial \bar{m}_t} / \frac{\partial U_t}{\partial t}$. Or, put differently, since the utility of both the subsidized and taxed groups decreases with the cost of political pressure (i.e., $\frac{\partial U_g}{\partial \bar{m}_g} < 0$), groups will actively make political demands so long as they are beneficial relative to the cost of doing so. The two broader groups (s, t) can each easily be extended to include several actors (sub-groups), with the larger budget constraint holding: though no individual actor will necessarily have their transfer offset one-to-one, the whole of the subsidy transfers must equal the whole of taxed transfers.[3]

A few specific concepts within this model are worth elaborating further. First, gains by actors receiving subsidies will be mitigated by the political pressure exerted by taxed groups, and that offsetting pressure will scale to the deadweight losses caused by those subsidies. The intuition behind this is that subsidies will generally create deadweight losses, following $G(.)$, which will increase taxes and, in turn, raise the political demands of the taxed group. The greater the distortion contained in $G(.)$, the greater the pressure by taxpayers.[4] Extending this analysis to many groups, then, it can be shown that the marginal increase in deadweight losses, G', will be proportional to the relative influence gained to the costs borne by each group. That is, actors that are more efficient at exerting influence can demand more distortionary payoffs. Showing this relationship for only two actors in the subsidized group, $i, h \in s$, this gives:

$$\frac{G_i'}{G_h'} = \frac{\partial \Theta_i / \partial m_i}{\partial \Theta_h / \partial m_h} \tag{5}$$

Intuitively, this means that an actor can receive more as a result of its demands if the marginal increase in deadweight loss is smaller, on one hand, but also if that actor is able to generate more influence relative to the cost of doing so (i.e. $\partial \Theta / \partial m$).

Empirically, none of the elements of Eq. 3 (or Eq. 5 by extension), can be directly observed.[5] We are interested in estimating political influence (Θ_i), which is an inherently unobservable—and thus latent—trait. Likewise, but perhaps less intuitively, we consider the transactional costs associated with political

[2]Specifically, for simplicity purposes the model applies a Cournot-Nash equilibrium.
[3]That is $\sum_{t=1}^{T} n_t G(\bar{t}) = \sum_{s=1}^{S} n_s G(\bar{s}$, for all taxed groups $t = 1, ..., T$ and subsidized groups $s = 1, ..., S$.
[4]Strictly, the taxpayer pressure also depends on the deadweight loss of $F(.)$.
[5]We limit our discussion to mainly focus on groups receiving subsidies as the primary actors.

pressure to be unobservable as well. Often costs will be direct, as in the case of political contributions, but these costs may not be reliably measured or hidden, for example in the case of the exchange of bribes and/or favors. The costs of political pressure may also be indirect. For instance, if a firm chooses to take collective action, involving other firms or interests, it risks an opportunity cost of those other actors diluting its demands (Shleifer and Vishny, 1994). This cost may arise even if other actors choose to remain politically inactive, resulting in a free-rider problem.

The larger point is that the mechanism in Eq. 3 implies that actors will attempt to minimize the associated costs of their political demands. In Becker (1983)'s framing, actors will seek to become more efficient at reducing free-riding, which is a problem when political demands are for non-exclusive 'collective' goods. In Olson (1965)'s seminal work, one solution for this problem is through coercing beneficiaries to share the costs of these demands (specifically in this case through membership in a political association). Another solution is for actors to seek out 'selective' goods, which can be doled out exclusively within a group or organization (Olson, 1965).[6] Demands for selective goods need not be limited within organizations: they can also take the form of other exclusive goods, such as preferential access to finance (e.g. Khwaja and Mian (2005)), or for that matter selective granting of permits or licenses. To the extent that actors realize net benefits, they may also develop preferences for (and possibly actively support) political systems that are receptive to their demands relative to those of other actors, including the public (Holcombe, 2018).

We limit our focus to the political influence of firms, specifically. This area has drawn substantial attention; however, it is often limited to analysis of one or so modes of exerting influence (and even then through *a posteriori* outcomes)—the most prominent being preferential treatment due to a direct political connection.[7] Though there are some studies that attempt to measure political influence more broadly, e.g. Desai et al. (2011), those rely on self-reported assessments of influence.[8] Our contention is that firms' political activity—which can be measured in some degree—will also contain information about their influence. This approach understands that, at a base level, such activity requires an interaction with a political actor. These interactions can be tightly or loosely defined, ranging from, e.g., a political connection to a firm's use of its size to apply public pressure or visibility as a means of political action.

The equilibrium conditions in Eq. 3 further imply that firms will choose those interactions that minimize costs relative to the marginal pressure and influence they command. Additionally, we have established that any actor, including firms, will operate under a political budgetary constraint. As a result, firms may need to choose between specific interactions, and they may find some political actions too expensive relative to the payoff. This is what Salamon and Siegfried (1977) term as the 'threshold

[6] We return to this point later in our discussion of how firms will experience differential benefits of membership in a business association, for example.

[7] A limited sample of prominent work in this literature includes findings on the patterns of political connections (Faccio, 2006) and the returns to firm value (Fisman, 2001), preferential access to finance (Khwaja and Mian, 2005), protection (in the form of capital controls, Johnson and Mitton (2003), corporate bailouts (Faccio et al., 2006).

[8] Specifically, Desai et al. (2011) use a vignette approach asking the degree to which firms believe the following have influence "a: your firm; b: other domestic firms; c: dominant firms or conglomerates in key sectors of the economy; d: individuals or firms with close personal ties to political leaders" (p. 147). Their measure is then calculated given $a - \frac{b+c+d}{3}$.

problem', and in our framework, it implies that not all interactions will be available to all firms, who may in turn choose different combinations of those interactions to garner some level of influence.

More formally, consider the series of political interactions that can occur between firms and public officials $j = \{1, ..., \mathbf{J}\}$. Indexing firms by i, then, the above equations imply that the influence from a specific interaction (Θ_{ij}) can be expressed as a function of not only the cost of that interaction, but also the interactions of other firms/actors (h). We also assume that the political influence from any one of a firm's political interactions will depend upon its whole series of political interactions ($\mathbf{J}'_{\mathbf{i}}$). On this last point, several examples come to mind: for instance a larger firm that is able to dominate the demands of a business association or a connected firm that is able to avoid paying bribes (or one that is targeted for bribes due to those connections). Together then, this concept can be expressed as:

$$\Theta_{ij} = f(m_{ij}, \mathbf{J_h}, x, \mathbf{J}'_{\mathbf{i}}) \tag{6}$$

where m_{ij} are the costs associated with each interaction. $\mathbf{J_h}$ is the series of interactions undertaken by other actors (h). The term is broad enough to encompass the relative deadweight losses of subsidies to i and h (as contained in Eq. 5) as well as the relative efficiency of other actors at generating political influence. We also include a cross term of the effects of all of a firm's (i) political interactions ($\mathbf{J}'_{\mathbf{i}\neq\mathbf{j}}$). That is, how much influence a firm realizes from one interaction will depend on the influence it also receives from other interactions (e.g., a particularly large and visible firm may not receive the same influence from a bribe since it could risk greater publicity and blowback). x represents other factors broadly, and it could include things like age, location, or even shared social networks, ethnicity, religion, or educational background with government officials. Total influence is then $\Theta_i = \sum_{j=1}^{\mathbf{J}} \Theta_{ij}$. A firm will, in turn, realize this influence by adopting a choice set of political interactions being represented by $\mathbf{Y_i} = [\mathbf{Y}_{i1}, ..., \mathbf{Y}_{ik}]$, where each $\mathbf{Y_i}$ is a k-length vector of choices for these interactions.[9]

To this point, we have mainly discussed how a firm will engage in political interactions *within* a political environment; a natural extension of this approach is to also examine implications *across* political environments. There is a recognition that all systems (even dictatorial ones) will operate under some level of political pressure (Becker, 1983). What is important, here, is how the relative transaction costs of both subsidized and taxed groups vary across different political environments. This ties our work as well to an extensive literature of transaction costs in firms' general operations.[10] Such costs—and the relative gain in influence—can vary by the nature of the actors, their collective interests, and the underlying political structure, the so-called 'rules of the game'.

In open and more accountable states, such as those limiting power through constitutional order, transaction costs for the popular interest will be dissipate and remain low, making widespread political

[9] A firm's simplest choice set is whether or not to use each point of political interaction, giving a decision space of a matrix of size $2^{\mathbf{J}} \times \mathbf{J}$, or equivalently, firms choose a combination of political interactions given by $\mathbf{Y_i} = [\mathbf{Y}_{i1}, ..., \mathbf{Y}_{i2^{\mathbf{J}}}]$.

[10] Of course, there is an extensive literature of transaction costs in firms' general operations; North (1990) is among the first seminal work to extend such a framework to politics. Other notable extensions of the *political* transaction costs of the firm include Acemoglu (2003); Frye (2017); Markus (2015); Haber et al. (2003); Parisi (2003). Holcombe (2018) elaborates this concept as well, including a useful discussion of earlier work.

engagement possible (Buchanan and Tullock, 1965; Mann, 1986; North and Weingast, 1989; Wittman, 1995). We treat such systems as lowering the general cost of taxpayers applying political pressure. As a corollary, singular, vested interests in such accountable environments will find it harder to change policies if they are at odds with popular sentiments. To do so will invite popular opposition, and thus, these interests will want to remain small relative to the size of the taxed group, as discussed above.[11] By contrast, in political systems that selectively distribute benefits to an elite few, the associated costs of political influence will be lower for those groups, allowing them exert political pressure and gain influence at lower transaction costs (Acemoglu, 2003; Svolik, 2015; Holcombe, 2018). We regard such systems as having a low responsiveness to popular interests, which in our framework raises the relative costs of exerting political pressure for taxed groups. This is the equivalent of loosening the constraint on the collective pressure exerted by all subsidized groups.

As a result, we should expect to see varying patterns of the overall *distribution* of political influence across different political systems with varying quality of governance: where governance is poorer, we would expect to see higher levels of influence broadly. By contrast, at higher levels of governance quality, there will be the equivalent of higher entry costs to political action, and firms will benefit by keeping the size of the subsidized groups small relative to the size of the taxed groups, so as to not trigger popular opposition. In the aggregate, this will favor firms (or subsidized actors) that are able to more efficiently exert influence and political pressure. This implies that political influence will be more *disperse* in political systems that are more open and accountable, with a select few actors exerting higher levels of influence.

We have given a limited but illustrative framework for understanding political influence in a broader context; in the process, we have also provided reasons for why we expect measures of how firms engage in political interactions, *in conjunction* to be informative of that influence. Put simply, a firm's realized choices of political activity reflect its underlying influence and the relative conditions under which that influence exists. The relative costs that are implied by different political environments, which we can broadly group under the category of governance, also give us a reason to look at how political influence is distributed across different economies. In the next sub-section, we present a measurement model for estimating Political Influence and then analyze the different aspects of these estimates.

2.2 The Measurement Model

To address political influence as a latent concept, formally, we adopt a measurement model approach to the data, which is described in more detail in Section 3. In the model, the data are considered as observed indicators of an unobserved (and thus latent) measure, which we have called Θ_i.[12] Specifically, we use a two-parameter model following from item response theory (IRT 2-PL model). The 2-PL model

[11] Becker (1983) cites this dynamic as the reason, for instance, why extensive subsidies are observed for small interests like U.S. sugar production, relative to a large and disperse taxed group.

[12] This dimension is often referred to in the IRT literature as ability, as is the case in analyses of IRT in the standardized test literature.

adopts a Bayesian approach since we are trying to estimate the likelihood of the desired parameters $(\Theta_i, \gamma_j, \beta_j)$ given the data (y_{ij}), as opposed to the likelihood of the observed data, given the values of the parameters. The desired likelihood is then given by:

$$Pr(\gamma_j, \Theta_i, \beta_j | y_{ij}) = \prod_{i=1}^{I} \prod_{j=1}^{J} g(\gamma_j \Theta_i - \beta_j) \tag{7}$$

In the equation, **J** can differ by indicator type and can include binary, categorical, ordinal, or continuous variables. The indicator type will also determine the appropriate link function, given by $g(.)$, with the most applicable in our model being $logit^{-1}(.)$ in the case of a binary response. While only two of our items (size and the level of government ownership) are continuous, some readers will see comparisons to more familiar, linear applications, for instance in the construction of an unobserved components model as in (Kaufmann et al., 2011) or factor-based analysis, such as principal components.[13]

The parameter γ_j is a so-called 'discrimination parameter' of an item. This parameter indicates the steepness of the prediction that any response is given, along the axis of the latent trait (political influence, θ_j). In the IRT literature, this variant is known as an ideal point model (Kubinec, 2019). These models are commonly used to estimate scores for, say, legislators' position on a scale of conservatism (or liberalism), where a steeper discrimination for a yes-no vote more quickly separates conservative-leaning lawmakers from liberal-leaning ones (Clinton et al., 2004). Importantly, we do not impose polarity constraints on the vector γ_j, so that the discrimination parameter can take on positive or negative values. In the example of using ideal point models as applied to legislators, a "yes" vote will be more likely for some pieces of legislation, the more conservative a legislator is (a positive discrimination); a "no" vote will be likelier for other pieces of legislation (a negative discrimination). For our purposes, not imposing a polarity constraint gives our model significant flexibility in whether the indicators negatively or positively predict influence. Rather than imposing an assumption on the model, we can learn from the model the likely polarity of the items in general equilibrium, as we described in the previous section. β_j (often called the 'difficulty parameter') here can be thought of as an item-specific average response for a respondent i with zero ability or an item j with zero discrimination. Since the intuition behind IRT models may be new to some readers, we provide an illustrative example of the behavior of both parameters in Results Appendix A.2.

There are two extensions to the standard ideal point model that we employ based on Kubinec (2019). The first is to allow the distribution of y_{ij} to vary by item. This is an important feature of the model as some of our firm-level measures, such as government ownership and firm size, are continuous in nature, while others are ordinal and binary (e.g., if a firm reports that it faced a request for a bribe payment). By jointly fitting different distributions, we can appropriately pool information across diverse types of measures.

[13] Kaufmann et al. (2011) note the early work by Goldberger (1972) on the use of unobserved components models in economics. This history runs parallel to the use of IRT in political science—for example in applications of ideal points among, say, legislators—however, the two approaches are fully compatible with the distinction of the link function of the item, which can be linear in applications of IRT.

Second, we employ the Kubinec (2019) method of adjusting for missing data. Missing data rates in firm surveys can be substantial, and in this case, we have reason to be concerned about non-ignorable missingness. Some firms may not want to report political activities they undertake, either because these are quasi-legal or illegal in their economy or because they do not trust the survey enumerators to keep their data private. As a result, missingness may be correlated with the latent trait, where either high or low influence firms may under- or over-report political activities and connections.

To adjust for this, we implement a two-stage IRT model to account for selection into item response. The first stage is a separate IRT equation with shared influence parameters Θ_i but different item parameters $\gamma_j^{'}$ and $\beta_j^{'}$. If a response y_{ij} is missing $y_{ijm=1}$, the posterior distribution is equal to the following:

$$Pr(\Theta_i, \gamma_j^{'}, \beta_j^{'} | y_{ijm=1}) = \prod_{i=1}^{I} \prod_{j=1}^{J} g(\gamma_j^{'}\Theta_i - \beta_j^{'}) \tag{8}$$

And if the survey response is observed $y_{ijm=0}$, we have the following posterior distribution:

$$Pr(\Theta_i, \gamma_j, \gamma_j^{'}, \beta_j, \beta_j^{'} | y_{ijm=0}) = \prod_{i=1}^{I} \prod_{j=1}^{J} (1 - g(\gamma_j^{'}\Theta_i - \beta_j^{'}))g(\gamma_j\Theta_i - \beta_j) \tag{9}$$

As such, the missingness mechanism allows for the observed responses to be either inflated or deflated depending on whether higher or lower values of the latent trait are correlated with missingness for a given item j, which is determined by the sign and level of the missingness discrimination parameter $\gamma_j^{'}$.[14] While relatively straightforward, this missingness adjustment will permit us to handle the most likely scenario in which highly influential firms are less likely to report political activities (or vice versa). Importantly, the missingness adjustment also means that our scores are defined over the whole sample regardless of how many responses each firm i answered. If missingness is ignorable for a given item j (a case in which $\gamma_j^{'} = 0$), the model will appropriately inflate the posterior variance of Θ_i to account for data that is missing completely at random.

On its own, the model will have multiple possible solutions to the values of the parameters, resulting in a multi-modal posterior (Bafumi et al., 2005). A common solution to this issue is to pin a specific item discrimination to an assumed value.[15] We choose to fix the discrimination parameter at 1 for a measure widely believed to give political influence: whether a firm has a direct political connection. Such connections have been extensively studied and shown to garner firms political favors and access, a point that was suggested above and elaborated more fully in Section 3. The discrimination parameters for the remaining items, γ_j, in turn can be interpreted relative to the discrimination given to that political connection. We do not constrain the sign of any γ_j, meaning there is a possibility for both a positive relationship—indicating complements—across items or a negative one—indicating substitutes.[16]

[14] This parameterization is essentially a hurdle model defined over a latent variable, where that variable represents item missingness in the data.

[15] Note that a pinned value of 1 is not the only possibility, nor is it limited to items. Individual units (i) may also be fixed. In the political science literature on ideal points and polarization, for example, legislators on either end of the political spectrum may be given fixed values (See Bafumi et al. (2005) and Clinton et al. (2004) for discussions. These approaches have also been extended to analyze the political leanings of judges as well (See Bonica and Sen (2021)).

[16] In the use of IRT models in standardized testing, for instance, discrimination parameters are lower-bounded by zero,

Lastly, it is straightforward in a Bayesian context to express Θ_i as a function of several predictor variables, so-called hierarchical co-variates. We denote the vector of these predictors as $\boldsymbol{X}_i^H$, which can be given parameter weights in a matrix ϕ', giving $\Theta_i = f(\boldsymbol{X}_i^H \phi')$ (Kubinec, 2019). This allows the measurement model to take advantage of a wide array of additional co-variates that are available in our data for the purposes of alleviating sparsity in the data. Because our survey has only one set of observations per firm, and the number of indicators is necessarily limited, estimating a separate intercept for each firm would result in unstable estimates highly dependent on the prior. By parameterizing Θ_i with additional survey data— $\boldsymbol{X}_i^H$ can include, for instance, firm perceptions of state-business relations— we can obtain stable predicted influence scores for an individual firm i with intercepts that vary by country and as such are robustly identified in the posterior. This underlying set of predictors also has the attractive feature of allowing for out-of-sample prediction from surveys without explicit political connections questions, allowing us to expand the index beyond the 41 economies in the original survey data. In the appendix we include a plot of split-$\hat{R}$ values from a model fit with three independent Markov Chain Monte Carlo (MCMC) chains with the Hamiltonian Monte Carlo sampler Stan (Carpenter et al., 2017). The plot shows excellent convergence of the dozens of parameters in the model. We also include a plot of residuals for the two continuous items, government ownership and employee size. This plot shows that the model's assumptions appear to be approximated by the distributions we assigned to the items.

The model does make an assumption of conditional independence. We assume that the responses for each firm are independent conditional on the country of the firm and all firm-level co-variates in the model. We believe this assumption to be met by design as the data were collected through a confidential survey around the same time, and firms did not have access to the responses of other companies. We also make a conditional independence assumption about items, though the assumption is weaker than for firms. By including two parameters for each item (that is, γ and β), we allow the discrimination and difficulty to vary by item.[17] It is still plausible that the items could interact with each other, but this is also why we emphasize the interpretation of the model parameters as marginal distributions. Adding interactions between item parameters would only be advisable if we had a theoretical reason to expect those interactions as it would significantly complicate the model's interpretation. The aim of this model is to permit theoretically informed measurement, not to maximize predictive performance.

3 Data and Measures of Political Interactions

Our data are from the World Bank/EBRD/EIB Enterprise Surveys (ES) in 41 economies in Europe, Central Asia, the Middle East, and North Africa (N=27,613). Section A.3 in the Data Appendix contains basic information about the samples in each economy. The surveys cover well-defined sectors in each economy, including manufacturing, construction, retail and wholesale trade, accommodation, transport,

since a correct response to a test question (item) is always expected to relate positively to ability. By not bounding direction, our approach follows the ideal points literature from political science (e.g. Clinton et al. (2004)), which estimates parameters on items that are, e.g. legislation, that may polarize politicians to either end of a political spectrum.

[17] See Appendix A.2 for an illustration.

and IT services. The data follow a complex survey design, with stratification defined by firm size,[18] sector, and location; the surveys carry sampling weights and, so, they are nationally representative of a substantial portion of the private sector economy.[19] The surveys use a standardized instrument and are conducted on an economy-by-economy basis, though they are frequently implemented in multi-economy roll-outs. We include all data from the most recent implementation of the surveys, conducted from 2018 through early 2020. Importantly, the surveys all include common variables that provide clear measures of interactions with public officials and a number of firm-level characteristics, including experiences of the broader business environment. Full details on the various means of political access (items) and other variables of interest are included below.

3.1 Items: The Political Interactions of Firms

Political connections

As noted above, we place specific importance on direct political connections. While a broad literature in both economics and political science has considered political connections directly, the definition of these connections varies substantially. One direct definition is if a politician holds a managerial or decision-making position in a firm (e.g. Faccio (2006); Khwaja and Mian (2005)). This direct definition can also be extended to include corporate Boards of Directors as well (Goldman et al., 2013). Still, others have extended the definition of political connections to close relationships that require specific context. Gomez et al. (1999), followed by Johnson and Mitton (2003), rely on a listing of firms with friendships and close ties to a handful of top leaders in Malaysia. Fisman (2001) uses a 'Suharto Dependency Index' in Indonesia. Rijkers et al. (2017) leverage a data set connecting firms to the holdings of the Ben Ali family in Tunisia. Likewise such connections can be extended to school networks, as well as close advisors and friends (see, for example, Bertrand et al. (2018)'s analysis in France). Kubinec et al. (2021) employ both self-reported political connections on a 1 to 10 scale and a measure of aggregated relationships between firms and the state; they find that the self-reported scale tends to be more theoretically valid than the aggregated observed measure.

The specificity of connections across several disparate economies, in turn, presents a challenge. The nature of connections in one economy may very well not translate to another. Take the role of the military, which may evoke a wide range of the meanings of political connections depending on the context of a specific place. Our need for a measure with plausible, directional consistency toward political influence, gives us a reason to favor a direct measure of connections that is widely applicable. For this, we define political connections using the measure from the survey: *Has the owner, CEO, top manager, or any of the board members of this firm ever been elected or appointed to a political position in this country?* We note that this measure is not necessarily ideal in the sense that it is not fully comprehensive. Previous

[18] Firm size is determined by the total number of workers and excludes firms with fewer than 5 workers. The size categories are small (5–19 workers), medium (20–99), and large (100+).

[19] The surveys' population of inference excludes certain ownership structures, such as non-profits or 100 percent government-owned establishments. For more details on the survey methodology, refer to the Data Appendix or see https://www.enterprisesurveys.org/en/methodology.

studies have illustrated that intensive knowledge of a given context can yield an economy-specific measure of connections, such detail is unlikely available across as wide of a range as the 41 economies included in our data. What is more, such connections are still likely to be measured with error vis-à-vis their ability to capture influence. Some connections may result in influence, others may not. The advantage of using an exploratory technique such as IRT is that it allows us to use the combination of several political interactions, with our measure of political connections as an anchor of sorts, as generally indicative of influence: that is, it frees us from relying on a single political interaction alone.

Government ownership

Our other items—that is the other means of gaining political influence—perhaps do not have as much ambiguity in their measurement as the indicator for political connections, but we may have reason to believe that they differently reflect underlying political influence.[20] Consider partial state or government ownership. We observe highly variable levels of government ownership across the 41 economies (see Table 1 below).[21] These patterns are unsurprising, as different governments have engaged in varying levels of either privatization or the 'corporatization' of state ownership, particularly given the large number of formerly centrally planned economies in our data set (Shirley, 1999). Often the exchange between firms with partial state ownership and politicians is framed as the latter taking advantage of the resources of private enterprise to enrich themselves or bolster their political position (e.g., Shleifer and Vishny (1994)). We also note that there can be a positive return to the firm from this ownership connection; this can occur through regulation restricting new entrants or, in the case of transitional privatization, through the choice and structure of the buyers the state chooses (Bennett and Maw, 2003). That is, *a priori*, we do not know whether to expect if state ownership will enhance or limit political influence.

Business associations and lobbying

Participation in business and industry groups can be seen as a balance between the private interests of firms, the transactional costs of collective action, and the ability to move political actors (Grossman and Helpman, 2001). To act collectively, business associations must overcome a natural inclination of private actors to passively benefit from like interests by free-riding in the absence of compulsion or specific, 'selective' goods (Olson, 1965). The incentives of those within such collective action groups will be to penalize and reduce free riding (Becker, 1983). In equilibrium, then, it is unsurprising that in many economies, membership in industry chambers, labor groups, and other associations is mandatory. It follows that different firms, including those with more or less influence, will draw different benefits that these associations confer, including providing key information, coordinating market actors, and even engaging in collective negotiations.

[20] We note that this is a restatement of the construction of the Measurement Model in 2.2, which pins political connections to 1, but does not impose any directional constraints on the discrimination parameters of other items.

[21] Note that the Enterprise Surveys require at least some level of private ownership to be considered eligible for the survey, and so firms with complete state ownership are excluded.

A central role that associations are assumed to play is to lobby on behalf of their members' interests (Haggard et al., 1997). In its most basic form, lobbying can be thought of, as Grossman and Helpman (2001) note, as a 'common agency problem', where like interests act as the principals, and the government is the agent. Therefore, we expect lobbying to be a transactionally expensive action from the perspective of this principal-agent problem and by diluting a firm's singular interests with the collective action of similar interests (e.g. as noted by Shleifer and Vishny (1994)). For some firms, this transactional cost will be dearer relative to its available options, for others it will be a cost of political action they bear willingly. That is, we expect differential payoffs to firms based on their underlying influence. We also expect that firms will value such lobbying differently as a result. Our data have two key measures along these dimensions. First, the surveys ask firms if they are a member of a business association of some type. Next, for those that are members of an association, the surveys ask how valuable firms find the lobbying services of the association. Again, we do not assume a directional relationship between either measure and Political Influence.

Corruption

Under various models, corruption is a means by which a political or public actor cedes some level of control in exchange for the extraction of rents (Ades and Di Tella, 1999). In this way, corruption can be a means of firms paying for political action. Corruption may be the cost of actualizing influence, and depending on context, paying bribes may be a comparatively cheaper option transactionally than, for instance, lobbying (Harstad and Svensson, 2011). This gives an expectation that corruption will be positively related to influence. On the other hand, extracted bribes may be the price of the absence of other means of political influence. When firms lack influence, they must pay bribes, giving an expectation of a negative relationship between corruption and influence. This is the perspective that firms will either purchase the 'capture' of state actors or through influence (Hellman et al., 2003). Political influence in this way is a means to reduce the otherwise expected rents, and thus cost, from firms to bureaucrats (Desai et al., 2011).

To accommodate that corruption and influence can interact in different ways, we consider two different measures of bribes between firms and public officials. The first is a general measure of whether firms expect that to 'get things done' in their day-to-day operation, they must pay bribes. The measure is general and not linked to specific transactions, and so we refer to it as *generalized corruption*. A second, related measure is whether firms encounter at least one specific bribe request in a series of transactions with government officials, a measure of so-called *bribery incidence*. While certainly related, the two measures cover slightly different concepts: more specifically, *bribery incidence* requires that firms engage in specific activities (like applying for a permit or license), and can thus be avoided or minimized if firms select not to engage in those transactions. In other words, a firm may avoid engaging with certain state-provided services altogether if they fear the required bribes, or a firm may engage in such interactions knowing full well the likelihood of a bribe as the price of completing the transaction. The *generalized* measure is not tied to specific transactions, then, to capture a broader, everyday level of required bribery.

Firm size

The importance of firm size follows directly from the political budget constraint laid out in Section 2.1; this is put succinctly by Salamon and Siegfried (1977), "What makes the absolute size of available resources, and hence firm size, so important politically is the fact that political involvement has certain fixed costs attached to it..." (p. 1031). Public visibility and status as a larger employer tends to go hand-in-hand with greater firm size (see early work from Salamon and Siegfried (1977) and also, e.g., Chong and Gradstein (2010)). At the same time, it is not clear that influence follows from firm size and not the other way around. For example, Bertrand et al. (2018) document that politically connected firms in France disproportionately hire workers to hold favor with local politicians.

The ES include information on full-time, permanent employment at the end of the previous fiscal year, as well as information on temporary (or seasonal) employees and their average duration of employment. We use a measure that includes both permanent, full-time employees in addition to the permanent, full-time equivalent of these temporary workers.

Descriptive statistics of items

Table 1 shows the mean values of the main political interactions in our model (the items). These are produced first by computing a survey-weighted average by economy and then taking the simple average across the 41 economies. The final two columns also show the minimum and maximum values at the economy level (i.e., the economy-level average that is lowest and highest, respectively). Our measure of political connections has a mean value of just under 5%, ranging from an economy-level average of just under 1% (Italy) to a notably high average of 28% (Tunisia). Both corruption measures have economy-level minimums at 0%, with maximums above a third of firms for both measures.[22] Membership in a business association averages at nearly 4 in 10 firms, with a minimum of 9% (Armenia) and a maximum of near universal membership in Croatia.[23] The share of firms finding their business association's lobbying as useful is 15%, with a minimum in Lithuania of under 3% and a maximum over 60% in the Arab Republic of Egypt.[24] The vast majority of firms, unsurprisingly, have no government ownership: in several economies the mean level of state ownership is 0, with an average level of government ownership in Belarus over 7%.[25] Overall, the average firm size is approximately 15 employees, and this average is lowest in Poland (9 workers) and highest in Azerbaijan (nearly 23 workers).

[22] Estonia and Malta have the lowest averages for the transactional and general corruption measures, respectively; while Ukraine and Morocco report the highest averages.

[23] This reflects the compulsory membership requirement in, for instance, the Croatian Chamber of Economy.

[24] This indicator takes a value of 1 if firms rate their business association's lobbying as 'somewhat' or 'very useful'. If a firm does not belong to a business association, it is coded a 0.

[25] In Armenia, Azerbaijan, Bulgaria, the Czech Republic, Estonia, Georgia, Jordan, Lebanon, Lithuania, and Portugal the average is 0%.

Table 1: Items: Political Interactions (Percentages)

	Mean	S.E.	Min.	Max.
Political position in management/ownership	4.9	0.3	0.7	27.9
Transactional corruption	9.8	0.6	0.0	37.4
General corruption	10.6	0.4	0.0	36.1
Member of business association	39.2	0.5	9.2	98.8
Bus. assn. lobbying useful	15.2	0.4	2.9	61.0
Share government ownership	0.3	0.0	0.0	7.2
Size (number of workers)[a]	15.0	1.0	9.4	22.5

[a] - full-time permanent equivalent.

We should note that our data are based on the actual responses of firms to survey questions. As with any data, these data measure certain concepts with noise. Such uncertainty in the measurement of concepts can occur in the measurement of sensitive topics, such as corruption, due to respondent reticence (Kraay and Murrell, 2016). Simultaneously, our items may imperfectly capture influence, *per se*, as would be the case of recording a firm with a true political connection, but one that does not yield much actual influence. Our contention is that each of our chosen items reveals valuable information about an underlying concept of influence, Θ_i: what our IRT-based approach allows is an extraction and estimation of this signal across several such items. This approach does not require us to make many prior assumptions about the relative direction and magnitude of these items, with the exception of our assumption about the role of political connections.

The underlying flexibility of this Bayesian approach, we believe, requires us to directly address issues of possible measurement error in our model. First, IRT allows us to add stability to our index measure by linking it to an underlying set of predictors, or hierarchical co-variates, which we describe in the Appendix.[26] These predictors link our measure of Political Influence to not only the items themselves, but also to a number of aspects describing the underlying business environment. Second, because we directly account for data that are missing for possibly non-ignorable reasons (as described in Eqs. 8 and 9), we can be more confident that the measure adjusts for sensitivity bias if respondents are uncomfortable answering certain questions. Lastly, and importantly, the estimated Political Influence index, as an expression of a series of posterior probabilities, is estimated with error. Given the reasons for possible mismeasurement that we have listed—non-ignorable missingness and imperfect measures of items and underlying predictors—we feel that it is also important to provide a measure of Political Influence measured with uncertainty. And, in fact, we consider our direct treatment of possible measurement error to be a strength of our approach, and so we include this measurement variability in our later analysis as a robustness check.

[26]The stability of the model is also shown in the split-$\hat{R}$ measures included in Appendix B.1, which show that the model achieves notably stable convergence, implying that it is robust to the choice of priors (Gelman et al., 2013; Carpenter et al., 2017).

4 Model Results

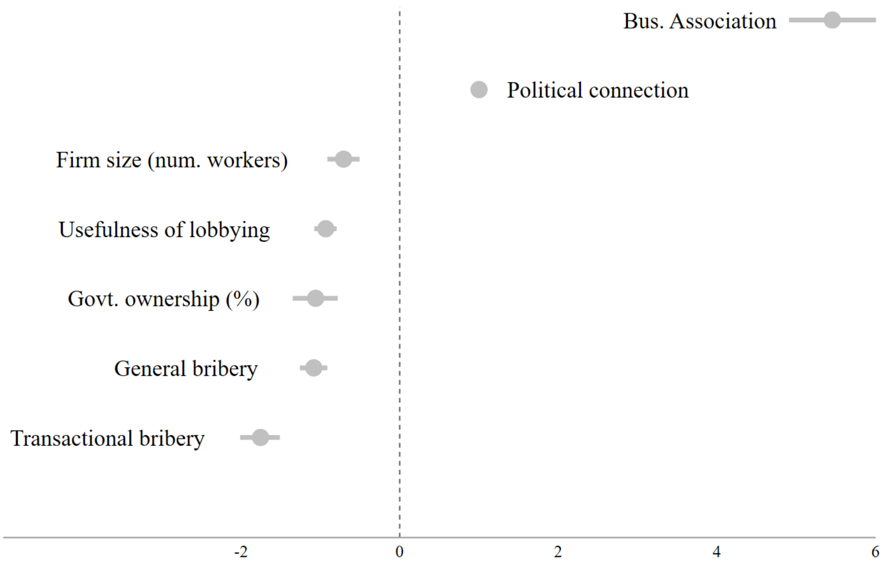
4.1 Item Discrimination

The estimated item discrimination parameters, γ_j from Eq. 7, are shown graphically in Figure 1. The median point estimates are shown, as well as the lower (the 5th percentile) and upper (95th percentile) quantiles of the empirical posterior estimates. Analogous to confidence intervals, this range of values can indicate a given level of statistical significance when these bounds exclude zero, shown by the vertical dashed line. In the previous section, we motivated our selection of items through our reading of a broad literature. However, a discrimination parameter indistinguishable from zero for any given item would make us cautious about our choice of political interactions since these parameters are an indication of each measure's ability to separate firms with low influence from those with high influence. The fact that the bounds of each of our items exclude zero is, in turn, a validation that we have selected relevant items that adequately separate firms with more influence from those with less. Recall, also, that we pin the discrimination parameter for reported political connections to 1 to identify the model, and that practically this reflects an underlying assumption that political connections are equivalent to unit discrimination. Generally, parameter values above zero indicate a positive, enhancing relationship with the latent characteristic of political influence, Θ_i; negative parameters, then, attenuate underlying influence.[27]

In terms of results, the model says that political influence is strongly reflected by membership in a business association—to an even greater magnitude than reported political connections. On the other hand, influence is attenuated by the other political interactions, including both forms of bribery, state ownership, and size. Interestingly, the more useful a firm finds the lobbying function of the business association, the less Political Influence it is likely to have. We take this finding as a suggestion that influential firms, while being members of business associations, do not need to rely on the collective lobbying of those organizations to achieve their political ends. This finding is also consistent with an understanding that influential firms may demand 'selective goods' (to the exclusion of other firms) from such organizations.

[27]We note as well that these discriminations take into account possible distortion arising from missing data, as we noted in the definition of the model.

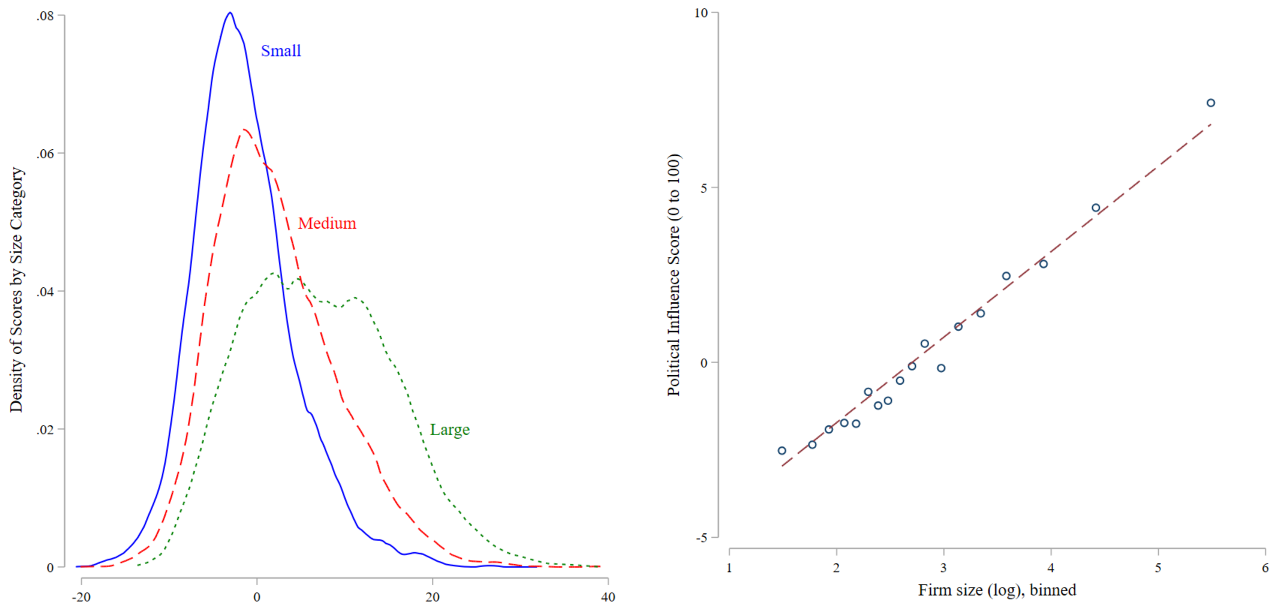
Figure 1: Item Discrimination Parameters



It is important to note that the discrimination parameters are marginal associations given the various combinations of political interactions. Consider the relationship between political influence and bribery, noting that both the 'general' and 'transactional' bribery parameters load significantly below zero. The model results indicate that, all else equal, a firm with greater underlying influence will be less likely to have a bribe extracted from it. Or alternatively, again assuming *ceteris paribus* conditions, a firm's influence will be reduced if it must pay bribes. In short, a connected firm is predicted to have less influence when it finds itself needing to pay bribes (all else equal) than one that does not. In this way, we consider those items as substitutes with respect to firms' underlying influence.

To analyze the discrimination parameters another way, note that each item itself is not predictive of the overall level of Political Influence. Any predicted score will reflect underlying items and characteristics as they are realized *in equilibrium*. Consider firm size, which has a negative loading as shown in Figure 1. This result does not mean that larger firms have lower Political Influence. To see this, we only need to look at the distribution of Political Influence by firm size, as in Figure 2. The figure clearly shows a *positive* relationship between firm size and the index. This recasts the discrimination parameters in a new light. Rather than show that smaller firms, on average, have greater Political Influence, the parameter implies that, all else equal, a more influential firm need not be as large. This finding lends itself to those of Shleifer and Vishny (1994) and Bertrand et al. (2018), who each show that political interactions may lead to rent extraction in the form of excess hiring by firms (where jobs for constituents or political friends can be thought of as a means of securing favor). The findings from our model are consistent with this mechanism, however they extend the analysis in an important way: greater influence can be thought of as a way of minimizing those rents that are extracted from the firm.

Figure 2: Distribution of Predicted Firm-level Political Influence by Size



Scores are mean posterior values, giving estimates of Political Influence (0–100). The left panel shows kernel densities of the Political Influence score by three size categories: small (5–19 workers), medium (20–99), and large (100+). The right panel shows a bin scatter of the log of firm size and Political Influence. Both figures are net of economy-level fixed effects and use survey weights, scaled by economy, so that they reflect the average relationship between influence scores and size within an economy.

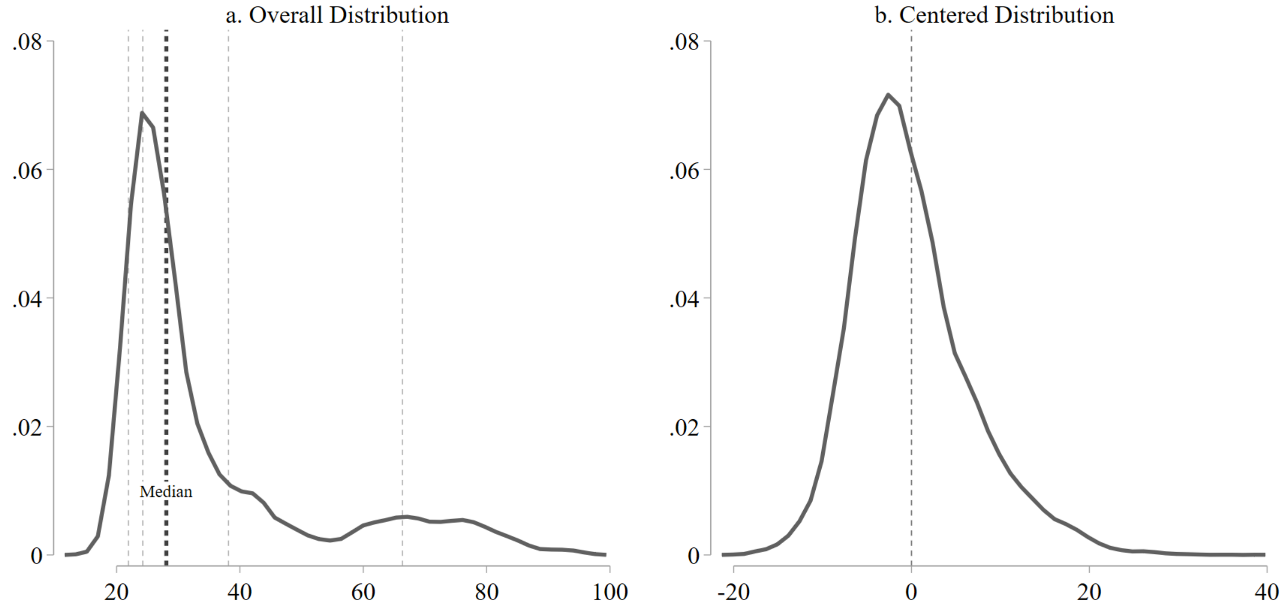
As mentioned above, our measurement model contains a first stage using a series of hierarchical co-variates. We present those co-variates in detail in the Appendix for completeness: Appendix A.4 describes the details of these variables in full, while Appendix B.2 gives the results from the first stage of the estimation.

4.2 Distributional Aspects of Political Influence

By producing a continuous Political Influence index—over nationally representative samples—we are able to not only analyze the levels of how firms engage politically but also the distributional aspects of our generated index. Figure 3.a. shows a kernel density of the raw scores across the 41 economies, with scores ranging from 0 (low political influence) to 100 (high influence). The vertical, dashed lines are the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution, with the median bolded for reference. The median value of Political Influence in our index is 28.3 (Table 2). The inter-quartile range is 13.7, but the range from the 10th percentile to the 90th is over 44 points, indicating a notable rightward skew in the distribution. In sum, then, our index indicates that the average firm is without much influence at all; it is only a small fraction of the firms that have notably high influence.

The distribution shown in panel a spans across all 41 economies in our data set , and so it can mask differences across economies. To give a sense of the average distribution of Political Influence within these economies, panel b centers the Political Influence in all economies around their economy-level median; that is, the panel shows the distribution of our index relative to the local economy average. In both panels, our Political Influence index shows that the modal firm is one with low to moderate influence, but, importantly, there is a notable rightward skew indicating that a small share of firms exerts notably high influence. This pattern holds both across all economies (panel a) and within economies (panel b).

Figure 3: Distribution of Political Influence Index (0-100)



Panel a shows the kernel density of estimated Political Influence across all 41 economies, using sampling weights. Panel b centers the index by subtracting the relevant economy median value of Political Influence. Since panel b is meant to show the average distribution *within* economies, the survey weights are also re-scaled to sum to 1 for each economy, to give each economy equal consideration.

Table 2: Summary Statistics across All Firms

		Percentiles					
	Mean	10th	25th	Median	75th	90th	S.D
Political Influence Score	35.2	22.1	24.3	28.3	38.0	66.2	17.0

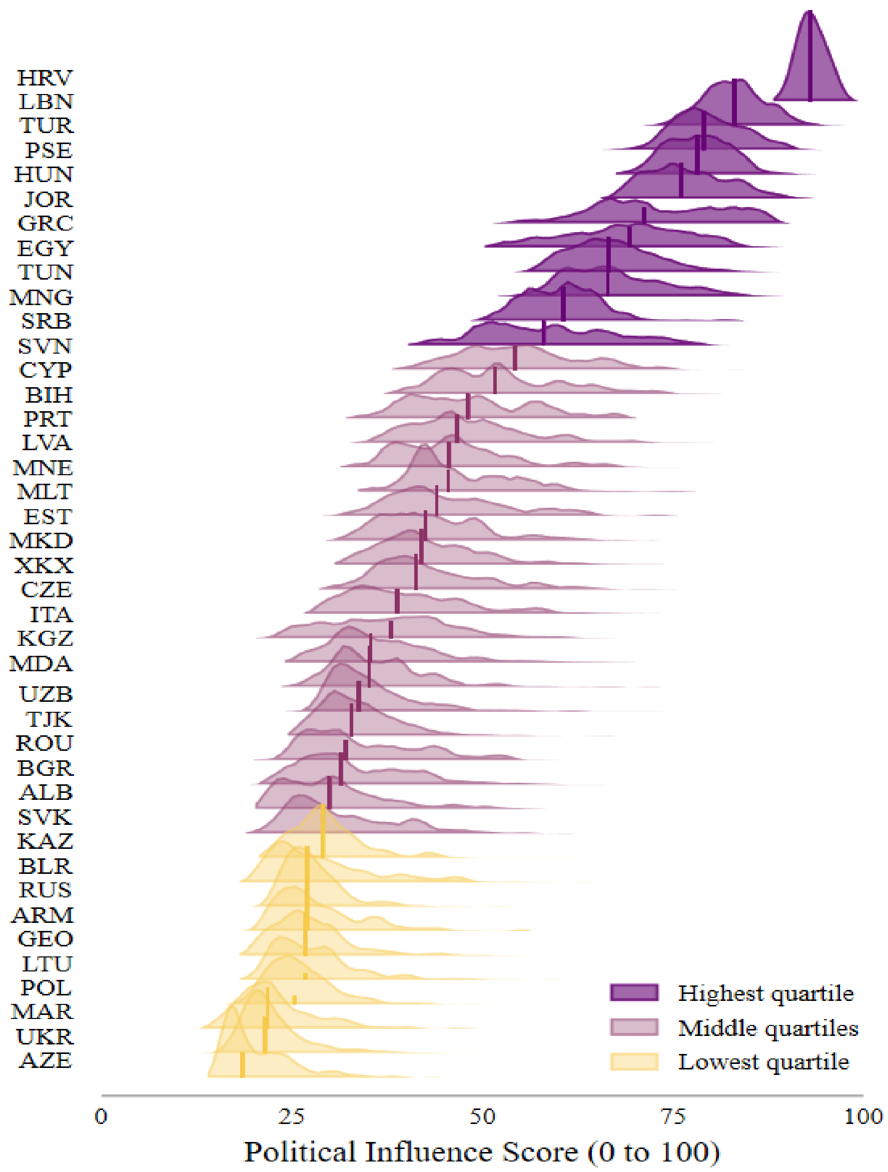
Each measure is indicative of the overall distribution across all economies, regardless of the firm location. All measures use sampling weights.

Figure 4 shows the distribution of the Political Influence Index for each of the 41 economies in our data. The economies are sorted in order by their median score in the index, which is represented by the vertical line in each distribution.[28] This ordering gives one sense of the relative averages of Political Influence across the data set —and to help illustrate the figure also shows the highest quartile (i.e., those economies with the highest median values) in the darkest (purple) shade, the middle two quartiles in a mid-color shade, and the lowest-scoring quartile in the lightest (yellow) shade. A quick look at the figure reveals that much of the differences in the distribution of Political Influence occurs *across* economies.

[28] All distributions are using kernel densities with bins of equal width, using sampling weights.

Still, we do observe substantial spread in Political Influence *within* economies as well. Table 3 includes a handful of measures of distributional spread across the 41 economies. On average, the ratio of the 75th percentile to the 25th is 1.2; the ratio of the 90th to 10th percentile is 1.5. These values indicate a substantial difference between the most and least influence firms *within* economies. However, the more striking finding is that this spread is substantially smaller than that across all firms, regardless of where they are located. That is, the equivalent ratios from Table 2 are 1.6 for the 75th/25th and 3.0 for the 90th/10th (also represented by the spread between the lowest and highest dashed lines in 3.b).

Figure 4: Distributions of Political Influence Scores by Economy



The figure shows the survey-weighted kernel densities by economy, with each economy-level median shown by the bolded, vertical line.

Table 3: Mean Summary Statistics Across All Economies

	10th to 90th		25th to 75th		
	Range	Ratio	Range	Ratio	S.D.
Political Influence Score	16.3	1.5	8.6	1.2	6.5

Each measure is an average across all 41 economies; that is, they are simple averages of survey-weighted averages within each economy.

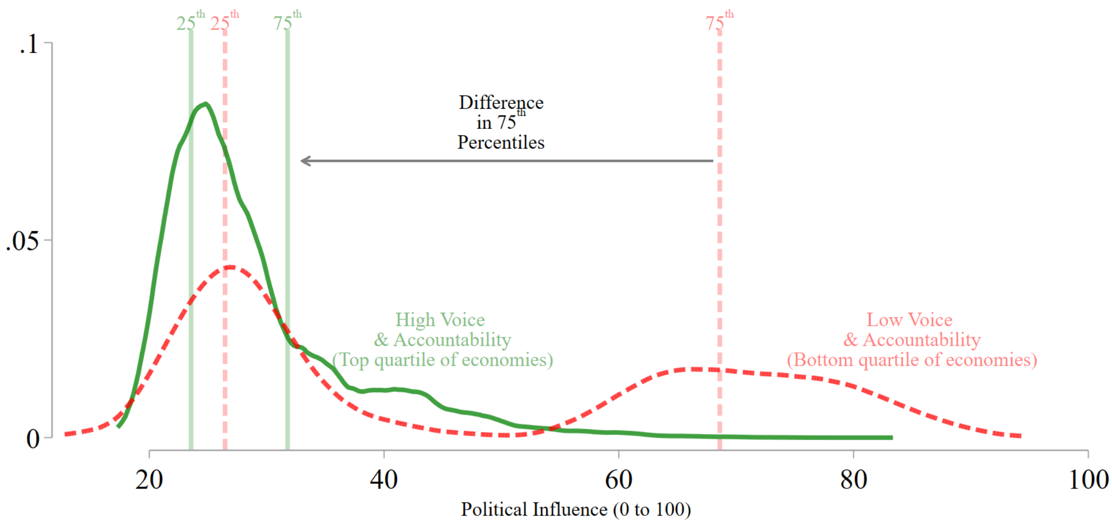
As we described in Section 2, given the costs of political action, we would expect certain distributional qualities in a well-measured index of influence. Specifically, the mass of political influence will be higher where the costs of using such influence is low, relative to broader interests—recalling that in our framing, lower relative costs follow from poorer governance. To investigate, we compare the distributions of Political Influence across various governance measures. We can, of course, use OLS to look at how the index varies by the average governance measure for each economy. However, OLS will only give an estimate of the co-movement of the mean of Political Influence with these governance measures. As we showed in Figure 3, the distribution of Political Influence has a long right tail; and so we may want to estimate the relationship between governance and Political Influence at different moments of the distribution. To do this, we use a different tool, known as unconditional quantile regression (UQR). UQR allows for the estimation of the relationship between a right-hand-side variable, in our case measures of governance quality, and the distributional aspects of Political Influence. These moments—often quantiles of a distribution—are descriptive of the realized distribution of Political Influence and are not conditional on specific, observed variables (like income level). The distribution of Political Influence surely results from several key economic and political factors, not just the measures of governance we present; and this means that the relationships between governance and influence are surely endogenous.[29] However, we feel this is the most appropriate way to express how Political Influence moves with different measures of governance, since it would be nearly impossible to claim that any other economy-level measure, say income level or legal tradition, is exogenous.

Since UQR and its interpretation may be unfamiliar to some readers, we provide a descriptive illustration of its aim here. Specifically, Figure 5 shows the distribution of Political Influence for two groups of economies in our data set . Those represented in green (solid lines) are economies in the top quartile of the distribution of the Voice & Accountability component from the Worldwide Governance Indicators; those represented in red (dashed lines) are in the bottom quartile. The figure also includes vertical lines showing both the 25th and 75th percentiles for both distributions. The movement between the different percentiles, in turn, gives an illustration of what UQR estimates. In this particular case, the figure shows a large and negative movement in the 75th percentile between the low Voice & Accountability economies

[29] Rios-Avila and Maroto (2020) provide a comprehensive and clear explanation of UQR and how it differs from what is typically called quantile regression, which they note is based on conditional distributions (and call CQR). They provide an illustrative example for using UQR, "For example, instead of trying to identify how an additional child affects earnings for single mothers with one child, researchers may be interested in analyzing the effect of every woman in the population having an additional child on the unconditional distribution of earnings."

and the highly-scored ones. Notably as well, there is a negative movement in the 25th percentile, but the difference is much smaller. In other words, the large improvement in governance represented by moving from the lowest-quartile economies to the highest-quartile ones shifts the distribution of Political Influence downward. However, the associated difference is much larger in the reduction of the rightward tail (that is the difference in the 75th percentiles is much larger than the difference in the 25th percentiles). Not only does this illustration show the intuition behind UQR, the relative magnitude of the two differences (at the 25th and 75th percentiles) provides an example of why it is important to look at these relationships over several parts of the distribution of Political Influence.[30]

Figure 5: Political Influence Distributions at High and Low Levels of Voice & Accountability



Firpo et al. (2009) provide a straightforward estimator for UQR using what is called a re-centered influence function (RIF). Rios-Avila and Maroto (2020) note that the RIF gives "...a first order approximation of the marginal effect of small location shift changes in the distribution of independent variables on any unconditional quantile", and that this approximation is possible by using the RIF as a left-hand-side variable using OLS (denoted as RIF-OLS). The RIF is defined as: $RIF(\Theta; q_\tau, F_\Theta) = q_\tau + \frac{\tau - \mathbb{1}\{\Theta_i \leq q_\tau\}}{f_\Theta(q_\tau)}$, where q_τ is the value of the index, Θ, at quantile τ and $f_\Theta(q_\tau)$ is the density of Θ at that given quantile. The function $\mathbb{1}\{\Theta_i \leq q_\tau\}$ takes a value of 1 if the value of the index is less than the cutoff given by q_τ, and 0 otherwise. Our two main estimations between governance quality and Political Influence are, in turn, given by:

$$\Theta_i = \beta_0^{OLS} + \beta_1^{OLS} GOVERNANCE_c + \varepsilon_i^{OLS} \tag{10}$$

$$RIF_i(\Theta; q_\tau, F_\Theta) = \beta_{0,\tau}^{RIF} + \beta_{1,\tau}^{RIF} GOVERNANCE_c + \varepsilon_i^{RIF} \tag{11}$$

where β_1 is the coefficient of interest. β_1^{OLS} is straightforward; $\beta_{1,\tau}^{RIF}$ gives the marginal movement

[30] In the Results Appendix B.3, we provide further descriptive and illustrative examples.

of a small change in GOVERNANCE on the quartile τ. The intuition behind UQR/RIF-OLS is worth repeating: a negative co-efficient on β^{RIF} implies that as GOVERNANCE increases, there is a downward shift in the distribution of Political Influence at a given moment (τ). The thing that will be of most interest to many—previewing our results—is the relative size of these coefficients. For example, a larger magnitude of coefficients at higher moments of the distribution (e.g., $|\beta^{RIF}_{\tau=75}| > |\beta^{RIF}_{\tau=25}|$), as illustrated in Figure 5), implies that changes in governance have a more dramatic relationship with the long rightward tail shown in our Political Influence Index, compared to movements at the leftward parts of the distribution.

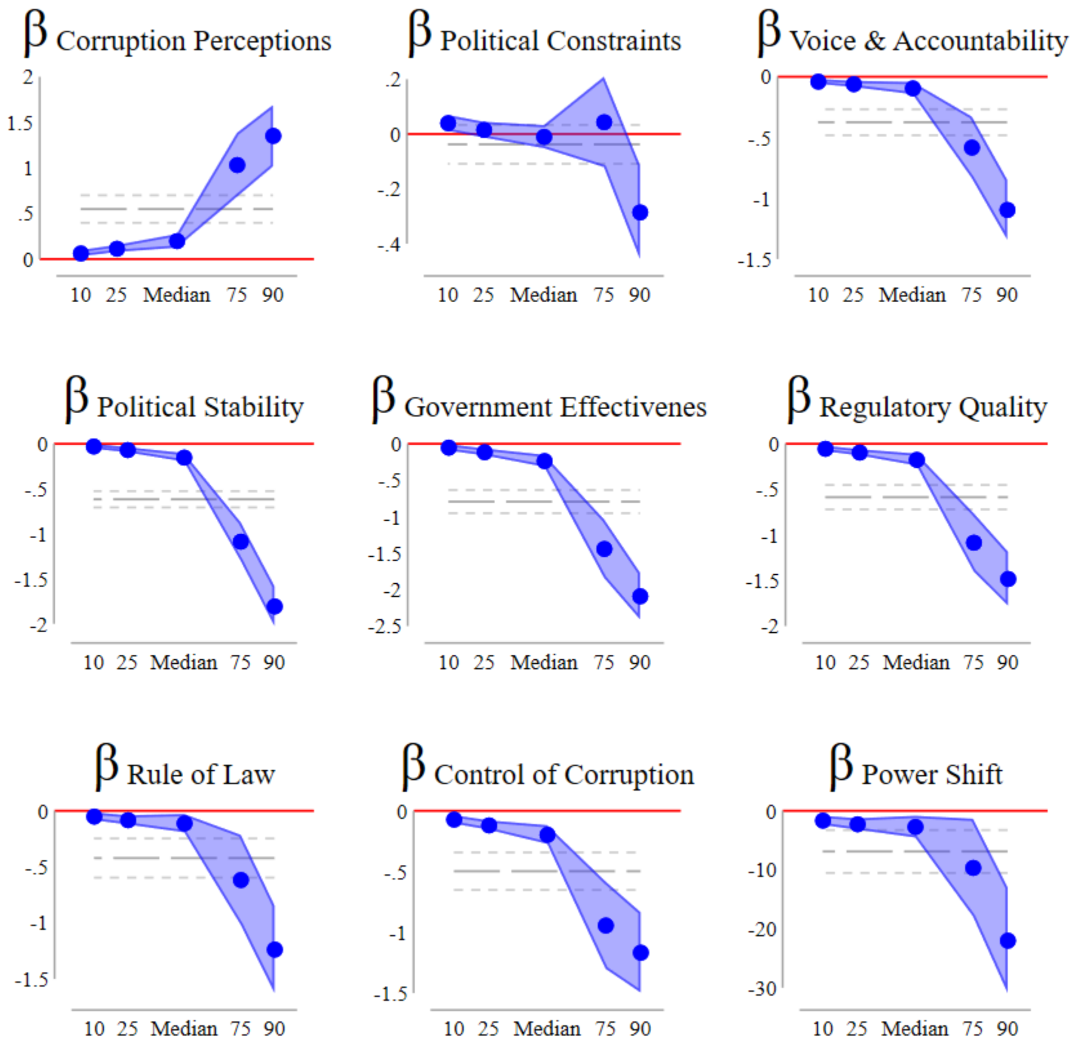
We use several well-known measures of governance quality to estimate the movement of Political Influence with the underlying political environment. These include Transparency International's Corruption Perceptions Index (CPI), which we reverse to have 0 indicate the lowest level of corruption and 100 the highest, as we find it more intuitive to have higher levels indicate greater levels of corruption. The second measure is Henisz (2002)'s political constraints score (POLCON), with higher values indicating more veto points in a political system, and thus more constraints on unitary action. Then, we take the six sub-indices from the World Governance Indicators (WGI), which include Voice & Accountability, Political Stability, Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption. For comparison with our index, we re-scale each of these sub-indices from 0 to 100, using the global minimums and maximums, where 100 indicates a higher level of governance quality.[31] Lastly, we include a dummy measure we denote as 'Power Shift' if there was a shift in executive power (excluding transitions where the same party retained power) in the last 5 years.[32]

Figure 6 graphically shows the results for a number of estimations following Eq. 10 and Eq. 11. All estimations use survey weights and use robust standard errors, adjusted for clustering at the level of stratum, to reflect the representative survey design (Abadie et al., 2017). The horizontal dashed lines (in grey) show the point estimate and 95% confidence intervals from the OLS estimates (β_1^{OLS}). The darker (blue) shaded area in each panel shows the point estimates and 95% confidence intervals from the RIF-OLS estimates, at the 10th, 25th, 50th, 75th, and 90th percentiles ($\beta^{RIF}_{1,\tau=10,25,50,75,90}$).

[31] Note this re-scaling is done for interpretation purposes. Kaufmann et al. (2011) note on the WGI website that the indices are in units of standard deviation, and range from -2.5 to 2.5. No economy in our data reports values outside of this range, and so we use the transformation: $100 * \frac{-2.5-subindex}{-2.5-(2.5)}$. The original score and the re-scaled one have a perfect correlation, and we run results on both the re-scaled score and the original sub-index(not shown).

[32] More details are provided in the Data Appendix.

Figure 6: β^{OLS} and β^{RIF} at Percentiles of the Political Influence Score



Recall that the interpretation of the β^{RIF} is the marginal change in the distributional statistic of our index of a 1-point increase in a measure of governance. To interpret these findings, it is helpful to return to the example of the Voice & Accountability sub-index from WGI. The mean score of Voice & Accountability is 50, and the sub-index has a standard deviation of nearly 18 across the 41 economies. Each point in Figure 6 represents the coefficient β_1^{RIF} from a different run of the RIF-OLS, at different moments of the distribution of Political Influence (i.e., $\tau = 10, 25, 50, 75, 90$), and so a fairly large increase in Voice & Accountability of +1 S.D. will result in the associated relationship of $\beta_{1,\tau}^{RIF} * 1S.D.$[33] The results then imply that a 1 S.D. increase in Voice & Accountability is associated with small (but statistically significant) reductions in the 10th and 25th percentiles of Political Influence, by 0.6 and 0.8, respectively. This 1 S.D. increase is also associated by a movement in the median of -1.6 points on the index. These small magnitudes make the movements of the 75th and 90th percentile even more notable: increasing governance

[33] We should note that RIF-OLS results are best interpreted over small changes in right-hand-side variables (Rios-Avila, 2020). For this reason, we present the RIF-OLS co-efficients in Figure 6; the exercise of multiplying by a 1 S.D. change should then only be regarded as illustrative for the purpose of interpretation.

quality (+1 S.D. in Voice Accountability) moves the 75th percentile down by 9 points and the 90th by over 19 (noting that this finding reiterates the illustrative example in Figure 5). Using this example to take a broader view of all the results shown in Figure 6, then, shows that as governance measures generally improve, the distribution of Political Influence shifts downward, with the most dramatic movements in the distribution occurring by reductions in the right-skewed tail of the distribution.

The results shown in Figure 6 show how the distribution of Political Influence overall moves with different measures of governance quality, regardless of the economy in which a firm is located. But, of course, firms exert influence relative to their immediate competitors. To look at how the distribution of Political Influence changes *within* economies as governance changes, we modify our RIF-OLS estimations. We specifically want to see how a firm's relative influence moves when compared to the average level of Political Influence in an economy. To do this, in Table 4, we re-present RIF-OLS estimates, but now, the left-hand-side outcome, RIF_i, is expressed relative to the median level of Political Influence in an economy.[34] This residual value is then treated as the left-hand-side variable in Eq. 11. Each specification again uses survey weights, only now these are re-scaled in order to give each economy a total weight of 1 in the pooled estimation. The estimated coefficients $\beta^{RIF}_{1,\tau=\{10,25,75,90\}}$ give the relationship between the governance measures of interest and the distance between the given percentile and the median level of political influence, on average, within an economy.[35] We also include a column labeled Movement, which shows the implied direction of the coefficients as each measure increases: $\longleftrightarrow$ indicates greater dispersion, $\rightarrow\leftarrow$ decreased dispersion, $\longleftarrow$ a shift lower (leftward), and $\longrightarrow$ an upward (rightward) shift in the index.[36]

[34]This of course is akin to including an economy-level fixed effect, however we choose to use the median value to bolster against outliers, particularly on the right tail of the distribution.

[35]By construction, the estimated coefficient with median $\tau = 50$ will equal 0; this is in fact the case in estimations, which we omit here.

[36]See also the illustrative example provided in the Results Appendix.

Table 4: RIF-OLS, Political Influence Relative to the Economy Median

	β^{RIF} at Percentile, $\tau =$				
	10th	25th	75th	90th	Movement
Corruption Perceptions Index (n=24,344)	0.043***	0.033***	-0.029*	-0.072***	$\rightarrow\leftarrow$
	(0.001)	(0.001)	(0.015)	(0.025)	
Political Constraints (n=23,923)	-0.011*	-0.012*	-0.013	-0.032*	$\longleftarrow$
	(0.007)	(0.006)	(0.011)	(0.018)	
Voice & Accountability (n=24,709)	-0.039***	-0.027***	0.015	0.048***	$\longleftrightarrow$
	(0.006)	(0.006)	(0.010)	(0.017)	
Political Stability (n=24,709)	-0.031***	-0.023***	0.015	0.067***	$\longleftrightarrow$
	(0.007)	(0.007)	(0.012)	(0.015)	
Government Effectiveness (n=24,709)	-0.031***	-0.018*	0.010	0.050**	$\longleftrightarrow$
	(0.011)	(0.010)	(0.015)	(0.024)	
Regulatory Quality (n=24,709)	-0.029***	-0.021***	0.016	0.039**	$\longleftrightarrow$
	(0.008)	(0.007)	(0.012)	(0.019)	
Rule of Law (n=24,709)	-0.045***	-0.030***	0.028**	0.068***	$\longleftrightarrow$
	(0.009)	(0.008)	(0.013)	(0.022)	
Control of Corruption (n=24,709)	-0.038***	-0.030***	0.019	0.054**	$\longleftrightarrow$
	(0.009)	(0.009)	(0.014)	(0.024)	
Power Shift = 1 (n=23,923)	-0.688**	-0.183	-0.551	-0.536	$\longleftarrow$
	(0.293)	(0.256)	(0.382)	(0.602)	

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$
To conserve space, R^2 has been omitted as have constants. Robust S.E.s are clustered at the level of survey stratum, within which firms were randomly selected (Abadie et al., 2017). All estimates are survey-weighted, with weights re-scaled so that each economy is equally considered, with weights in each summing to 1 by economy.

The results shown in Table 4 add a dimension to those shown earlier in this section: specifically, as various measures of governance improve, the RIF-OLS coefficients imply that lower percentiles move further away from the local median, and simultaneously the upper tail (above the 90th percentile) distances itself from that same median. That is, at levels of improved governance, the dispersion of Political Influence increases (Movement $\longleftrightarrow$). This point is made more boldly by its contrast with the coefficients on Transparency International's corruption perceptions measure. As corruption increases, dispersion in Political Influence decreases (Movement $\rightarrow\leftarrow$). Lastly, two measures on the structure of the political environment illustrate the relationship between structural components and Political Influence. In economies with a greater number of political constraints, relative Political Influence shifts downward (Movement $\leftarrow$); the same is the case for economies that have experienced a recent shift in political power. The fact that we observe lower overall levels of Political Influence in environments with more political constraints or ones that have recently had a transition in power suggest that Political Influence may wane when firms have to navigate a more complex political environment, where it is harder to get things done, and firms may also have lower general influence where political power has recently changed hands.

The end result is that poorer governance has a compressing effect, while improved governance widens an economy's relative distribution of Political Influence. This may seem counter-intuitive, as often political advantage is framed as influence doled out to a select few firms or interests. However, in the framing that we laid out at the beginning of the paper, these relationships can be squarely understood. If, as governance improves, one would expect openness and the balancing of interests (including the public *writ large*), so too would one anticipate higher entry and transaction costs to exert political influence. To generalize, the conceptual framework laid out at the beginning of the paper seems to undergird a finding in the data itself: open, transparent, and pluralistic governance renders political influence more expensive, resulting in fewer firms exerting such influence, and a broader distance between the most and least influential. In combination with our finding that the overall distribution of Political Influence tends to be higher in environments with diminished governance, these results imply a relationship where influence is greater on average in contexts that allow it to be exerted relatively freely, but that such political pressure will be met with often competing firms attempting to compensate for such influence themselves.[37]

4.3 Political Influence and Firm-level Outcomes

In this sub-section we present firm-level estimates of the relationship between our index and key outcome variables. Following from several earlier works (e.g. Hillman (1982); Becker (1983); Grossman and Helpman (1994)), we consider that the exertion of influence creates a deadweight loss to public welfare, and that this loss is a cost to politicians, who risk retribution from the public; it is a benefit to the firms, who are thus willing to expend influence to secure those gains.[38] As previously established, we expect more accountable governance to extract dearer costs from politicians who allow or contribute to larger deadweight losses. We consider that the principal way firms realize the spoils of their influence is through demanding protection from competition, either through the restriction of new entrants or, commonly, through trade protectionism. This means that competition is likely oligopolistic, where firms are few and affect others, settling into a Cournot-Nash equilibrium (see Becker (1983)). That is, our expectations follow recent work on market power—in this case, emerging from influence. In this framework, we expect market competition to be limited, larger revenues to accrue to fewer firms, but for those revenues to be realized with less intensive input use, e.g. through a lower labor cost share of production (De Loecker et al., 2020).

Table 5 presents several regressions using the generic OLS form:

$$Y_i = \beta_0 + \beta_\Theta \Theta_i + \boldsymbol{\beta_x} \boldsymbol{X} + \varepsilon_i \tag{12}$$

where Y_i is one of four key outcomes. First, we include a dependent dummy variable that equals 100 (scaled for the easier interpretation of results) if a firm reports that in its main market it faces fewer than 20 competitors.[39] The second key outcome variable is the log of total sales, standardized to 2009 USD.

[37] Some readers will note that such barriers to entry (here, the higher relative cost of political influence in higher governance environments) and transactional costs mimic the industrial organization literature on productivity dispersion.

[38] Hillman (1982) and Grossman and Helpman (1994) establish these gains particularly in the form of trade protectionism.

[39] The ES data include a question that asks respondents to list the number of competitors they face in their main market, which included a pre-coded option of "too many to count". The cutoff of 20 corresponds to the average median value of

This is followed by two output variables scaled to labor inputs: first is the log of sales per worker (i.e. labor productivity), again in 2009 USD, followed by the ratio of total labor costs to total revenues. The latter three outcomes all are trimmed of outliers.[40] $\boldsymbol{X}$ is a vector of co-variates including the log of the age of the firm, the years of experience of the top manager, and dummy variables of whether the firm has at least 10% or more foreign ownership, exports 10% or more of its sales, and if it is part of a larger firm.[41]

These specifications are cross-sectional and surely endogenous. However, we have some reason to believe that some specific sources of endogeneity will be mitigated. Since our Political Influence index score is estimated as a latent construct, based on the combination of items and firm-level characteristics across all firms in our sample, the risk of a firm-level co-variate affecting both the measure of Political Influence and an outcome of interest is low. This is not the case, when, for example respondent-level reticence affects both left-hand side outcomes and the measurement of a key independent variable. Likewise, we expect the risk of co-determination or simultaneity to be low, as our key explanatory variable is the result of our estimated model.

The most present risk of endogeneity with our index, then, is error correlated with some or many omitted variables. We partially address this by using various levels of fixed effects in $\boldsymbol{X}$: Cols. 1 and 2 include within-economy regional dummies[42] and 2-digit ISIC sector fixed effects. We think it is reasonable to assume that most exertion of Political Influence will, at a minimum, have implications in a firm's industry and location, and so we choose to use these fixed effects as our baseline.[43] To allow for the possibility that the analytical level that matters is the *intersection* of location and industry, we also include a series of interacted fixed effects in Cols. 3–5. To avoid sparsity concerns, Col. 3 interacts economy-level fixed effects with 2-digit sector effects; Cols. 4 and 5 interact more disaggregated location fixed effects with those sector effects. The most saturated estimation is presented in Col. 5, which interacts all co-variates—with the exception of fixed effects—in $\boldsymbol{X}$ with the Political Influence score, allowing for these adjustments to change based on the estimated index score. All specifications use survey weights, and these are normalized to give each economy equal weight, as we are concerned with the average relationship of political influence within economies. Standard errors use two-way clustering following Cameron et al. (2011), either at the economy-sector or the location-sector level, depending on the assumption of the included fixed effects, and thus our assumption of the application of where firm-level influence is relevant.[44] As an additional robustness check, in the Results Appendix B.5, we explore how these relationships differ based on underlying governance by interacting the Political Influence score

competitors in firms' main market, when the option 'too many to count' is assigned the maximum value.

[40] See Data Appendix for details.

[41] Note that throughout we use the term 'firm' for simplicity, but that the ES surveys establishments, meaning that an establishment can be part of a larger firm.

[42] Specifically, these are the regional strata determined by each economy's survey design, often corresponding to known geographical aggregates, such as the Nomenclature of Territorial Units for Statistics (NUTS) in main European countries, though the aggregation level may vary.

[43] Both levels of fixed effect are nested within more aggregate variables, for instance location within economy, or a 2-digit industry—such as food manufacturing—within a broader sector, e.g. manufacturing).

[44] Note that per Abadie et al. (2017), we also ran these specifications clustering S.E.s at the level of survey stratum; the two-way clustering generated larger S.E.s and thus is more conservative, and so we present those results here.

with economy-level measures of governance.

Table 5: Political Influence, Competition and Output

Fewer than 20 competitors (Y=100)	(1)	(2)	(3)	(4)	(5)
Pol. Influence	0.357**	0.311**	0.274**	0.383***	0.366***
	(0.136)	(0.124)	(0.104)	(0.108)	(0.0962)
Constant	31.34***	29.68***	31.79***	28.56***	29.43***
	(6.122)	(5.482)	(4.528)	(4.330)	(4.723)
Observations	21,633	21,633	21,518	20,750	20,750
R-squared	0.193	0.195	0.284	0.361	0.361
Total Sales (log 2009 USD)					
Pol. Influence	0.0775***	0.0704***	0.0724***	0.0716***	0.0589***
	(0.00540)	(0.00604)	(0.00704)	(0.00752)	(0.00646)
Constant	9.313***	9.428***	9.349***	9.381***	9.928***
	(0.244)	(0.252)	(0.298)	(0.321)	(0.308)
Observations	20,687	20,687	20,570	19,796	19,796
R-squared	0.337	0.352	0.430	0.493	0.495
Sales per Worker (log 2009 USD)					
Pol. Influence	0.0234***	0.0215***	0.0234***	0.0215***	0.0152***
	(0.00335)	(0.00444)	(0.00472)	(0.00460)	(0.00306)
Constant	9.144***	9.310***	9.246***	9.344***	9.610***
	(0.150)	(0.170)	(0.182)	(0.180)	(0.124)
Observations	20,540	20,540	20,424	19,649	19,649
R-squared	0.414	0.418	0.496	0.557	0.557
Labor Costs to Sales Ratio (log)					
Pol. Influence	-0.0131***	-0.0132***	-0.0150***	-0.0146***	-0.0168***
	(0.00293)	(0.00412)	(0.00464)	(0.00485)	(0.00317)
Constant	-1.318***	-1.328***	-1.273***	-1.288***	-1.192***
	(0.130)	(0.174)	(0.182)	(0.203)	(0.159)
Observations	18,653	18,653	18,533	17,724	17,724
R-squared	0.176	0.177	0.289	0.380	0.381
$\boldsymbol{X}$ co-variates		✓	✓	✓	
$\boldsymbol{X}$ interacted w/Pol. Influence					✓
Location FEs	✓	✓	✓	by Sector	by Sector
Sector FEs	✓	✓	by Economy	by Location	by Location

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$
OLS estimates. Robust standard errors, with two-way clustering at the 2-digit ISIC and region level in parentheses, per Cameron et al. (2011). Co-variates (not shown) include the log of age, the years of the manager's experience, dummy variables for exporters, foreign-owned firms, and those part of a larger firm.

The results from Table 5 confirm general expectations. Higher levels of influence are associated, robustly, with a higher likelihood of having a low number of competitors. While this is only a rough indication of the restricted competition demanded by more influential firms, it is notably significant across all specifications, even when adjusting for sector-by-location fixed effects, which would partial out any unobserved confounders at that level, including those that are localized within an industry-location, a level at which we would expect influence to be important. Likewise, more influential firms, by our measure, command greater amounts of revenues across all specifications. Importantly, they also do so at lower levels of demanded input, either the number of workers, as shown in panel c., or the total estimated labor cost relative to revenues; that is, more influential firms on average have a lower relative share of employment costs.[45]

How do our estimates of Political Influence compare to the direct measure of connections included in the data? To facilitate this comparison, in Table 6, we provide the marginal effects of an increase of one standard deviation of political influence, a change of roughly 6.5 on the index.[46] These marginal effects are presented alongside the same marginal effect of having a political connection, compared to no such connection. Recall that our index is pinned to this political connection value, but the measurement model allows for finer differentiation of when such connections are more likely to result in more or less political influence. While the direct comparison of a 1 S.D. increase of the influence index and the marginal effect of having a political connection are not directly comparable, the table does provide a ready comparison of the two measures relative to the given outcomes.

Table 6: Marginal Effects of a 1 SD Increase in Political Influence Compared to Political Connections

a. Fewer than 20 competitors (Y=100)	(1)	(2)	(3)	(4)	(5)
Marginal Effect +1 SD in Index	2.384**	2.074**	1.826***	2.555***	2.442***
p-val.	0.013	0.017	0.013	0.001	0.001
Marginal Effect of Political Connection	6.453***	6.018***	8.464***	9.080***	33.96***
p-val.	0.006	0.010	0.001	0.002	0.009
b. Total Sales (log 2009 USD)					
Marginal Effect +1 SD in Index	0.517***	0.470***	0.484***	0.478***	0.394***
p-val.	0.000	0.000	0.000	0.000	0.000
Marginal Effect of Political Connection	0.216***	0.146*	0.155*	0.243***	-0.508
p-val.	0.009	0.073	0.055	0.004	0.201
c. Sales per Worker (log 2009 USD)					
Marginal Effect +1 SD in Index	0.156***	0.144***	0.156***	0.144***	0.102***
p-val.	0.000	0.000	0.000	0.000	0.000
Marginal Effect of Political Connection	-0.060	-0.067	-0.057	-0.001	-0.078
p-val.	0.274	0.269	0.279	0.989	0.655
d. Labor Costs to Sales Ratio (log)					
Marginal Effect +1 SD in Index	-0.088***	-0.088***	-0.100***	-0.097***	-0.112***
p-val.	0.000	0.003	0.003	0.005	0.000
Marginal Effect of Political Connection	0.001	0.014	0.027	-0.026	0.237*
p-val.	0.989	0.796	0.651	0.614	0.067
$\boldsymbol{X}$ co-variates		✓	✓	✓	
$\boldsymbol{X}$ interacted w/Pol. Influence					✓
Location FEs	✓	✓	✓	by Sector	by Sector
Sector FEs	✓	✓	by Economy	by Location	by Location

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$
OLS estimates. Robust standard errors, with two-way clustering at the 2-digit ISIC and region level in parentheses, per Cameron et al. (2011). Co-variates (not shown) include the log of age, the years of the manager's experience, dummy variables for exporters, foreign-owned firms, and those part of a larger firm.

These results show that while political connections are related to a higher likelihood of having fewer

[45] See De Loecker et al. (2020) for an extensive discussion.
[46] This figure is average economy-level standard deviation across the 41 economies.

competitors, we do not find consistent and significant results when relating those connections to the other key outcomes of interest, total sales, sales per worker/labor productivity, and cost share of labor; we do find consistent and significant results for our index of political influence by contrast. That is, our results suggest the estimated Political Influence index, first, gives us a reliable measure of such influence, but secondly, that it does so by disentangling the cost borne by some 'connected' firms that have comparatively less ability, through influence, to stave off the costs of those connections; an example of which is a greater employment input as shown by the results for connections in Sales per Worker and the labor costs to sales ratio (noting that such findings would be consistent with, e.g., Bertrand et al. (2018)).

4.4 Robustness: Accounting for Error in the Political Influence Score

One potential problem with our estimations is introduced by the likelihood of measurement error in our estimated index. Indeed, this index is measured to express uncertainty, which we believe is a strength as it reflects estimated error in the latent construct—this is uncertainty which is not formally expressed in most measures of, e.g., political connections, which are binary. This error is idiosyncratic to the firm, meaning that we cannot simply assert that mis-measurement in the index will result in attenuation bias. For this reason, we do not estimate a commonly used error-in-variables model. Rather, since the firm-level index is estimated with a distribution of posterior values from the IRT 2-PL model in Eq. 7, we believe we can present plausible bounds of the estimated coefficient, based on varying assumptions of mis-measurement.[47] To do this, we present the same estimations run with values of Θ at the 5th, mean, and 95th percentiles (each specific to the firm, i).

[47] Formally, assume a noise parameter, α_i, high enough that when added to the true value of Θ_i, the mis-measured value of influence (Θ_i^*) is always greater than the true value: $\Theta_i^* = \Theta_i + \alpha_i; \alpha_i \geq 0$. In these cases, the bias between β_{Θ^*} and β_Θ will depend on $COV(\Theta_i, \alpha_i) + VAR(\alpha_i)$, (assuming that $COV(Y_i, \alpha_i) = 0$). If that sum is positive, there will be attenuation bias; if negative, β_{Θ^*} will be biased away from 0.

Table 7: Measurement Model Coefficients over Different Values of Political Influence (Θ_i)

Fewer than 20 competitors (Y=100)	(1)	(2)	(3)	(4)	(5)
$\beta_{\Theta,5^{th}percentile}$	0.369**	0.331**	0.295**	0.402***	0.381***
	(0.137)	(0.134)	(0.114)	(0.122)	(0.108)
$\beta_{\Theta,mean}$	0.357**	0.311**	0.274**	0.383***	0.366***
	(0.136)	(0.124)	(0.104)	(0.108)	(0.0962)
$\beta_{\Theta,95^{th}percentile}$	0.345**	0.289**	0.249**	0.357***	0.344***
	(0.136)	(0.123)	(0.107)	(0.107)	(0.0959)
Observations	21,633	21,633	21,518	20,750	20,750
Total Sales (log 2009 USD)					
$\beta_{\Theta,5^{th}percentile}$	0.0238***	0.0221***	0.0239***	0.0220***	0.0160***
	(0.00346)	(0.00464)	(0.00497)	(0.00489)	(0.00329)
$\beta_{\Theta,mean}$	0.0234***	0.0215***	0.0234***	0.0215***	0.0152***
	(0.00335)	(0.00444)	(0.00472)	(0.00460)	(0.00306)
$\beta_{\Theta,95^{th}percentile}$	0.0230***	0.0210***	0.0230***	0.0211***	0.0145***
	(0.00323)	(0.00417)	(0.00443)	(0.00428)	(0.00283)
Observations	20,540	20,540	20,424	19,649	19,649
Sales per Worker (log 2009 USD)					
$\beta_{\Theta,5^{th}percentile}$	0.0792***	0.0728***	0.0749***	0.0743***	0.0624***
	(0.00551)	(0.00622)	(0.00732)	(0.00779)	(0.00668)
$\beta_{\Theta,mean}$	0.0775***	0.0704***	0.0724***	0.0716***	0.0589***
	(0.00540)	(0.00604)	(0.00704)	(0.00752)	(0.00646)
$\beta_{\Theta,95^{th}percentile}$	0.0757***	0.0678***	0.0698***	0.0688***	0.0556***
	(0.00527)	(0.00580)	(0.00673)	(0.00724)	(0.00623)
Observations	20,687	20,687	20,570	19,796	19,796
Labor Costs to Sales Ratio (log)					
$\beta_{\Theta,5^{th}percentile}$	-0.0135***	-0.0139***	-0.0154***	-0.0149***	-0.0175***
	(0.00297)	(0.00421)	(0.00482)	(0.00502)	(0.00336)
$\beta_{\Theta,mean}$	-0.0131***	-0.0132***	-0.0150***	-0.0146***	-0.0168***
	(0.00293)	(0.00412)	(0.00464)	(0.00485)	(0.00317)
$\beta_{\Theta,95^{th}percentile}$	-0.0128***	-0.0127***	-0.0147***	-0.0144***	-0.0163***
	(0.00288)	(0.00398)	(0.00443)	(0.00463)	(0.00290)
Observations	18,653	18,653	18,533	17,724	17,724
$\boldsymbol{X}$ co-variates		✓	✓	✓	
$\boldsymbol{X}$ interacted w/Pol. Influence					✓
Location FEs	✓	✓	✓	by Sector	by Sector
Sector FEs	✓	✓	by Economy	by Location	by Location

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$
OLS estimates. Robust standard errors, with two-way clustering at the 2-digit ISIC and region level in parentheses, per Cameron et al. (2011). Co-variates (not shown) include the log of age, the years of the manager's experience, dummy variables for exporters, foreign-owned firms, and those part of a larger firm.

The results in Table 7 show that the estimates given in Table 5 are likely robust to measurement error in our index. All coefficients for the mean values of the index lie firmly within the bounds given by estimating Eq. 12 by using the 95th and 5th percentile values of the index; the former providing a bound of the coefficient closer to 0, the latter a larger-magnitude value of the estimates.[48] Similarly, the

[48]For a discussion, see the Data Appendix A.6.

magnitude differences between these coefficients and the mean score are generally quite small, adding additional reason to believe that results are not driven as a result of measurement error in the index.

4.5 Robustness: Firm-level Influence and Relationship to Peer Firms

The cross term in 6 implies that the net utility of any given political interaction is realized relative to the influence of other firms. Such choices for realizing influence lend themselves to a Cournot-Nash equilibrium—both in terms of the influence or political pressure applied as in Becker (1983)—but also in the oligopolistic outcomes in very recent work (see, for example, De Loecker et al. (2020)).[49] The higher dimensional specifications we offered above include (in Cols. 4 and 5) fixed effects at a level over which one could expect influence to be salient: in a firm's particular industry in a firm's given location. This also lends itself to a more demanding specification where we estimate outcome variables for a spatially determined outcome for firms h that are in the same industry-region, but excluding firm i, $h \neq i$. That is, if political influence is exerted in ways we expect, we also should see effects on the competing firms that are indexed by h.

Table 8 provides estimations from Eq. 12, using Y_h as the series of outcome variables. In this way, we move the relationship between Θ_i and outcome variables outside firm i. This means that these estimations will remove one type of omitted variable—for instance firm-level mis-reporting or reticence. However, they can likely introduce another, as there is a good chance that the distribution of Y_h will affect firm-level influence. Still, this is a more demanding specification, and one which will add depth to our results if we see a knock-on effect of influence on competing firms. Note that the specification is demanding in other ways as well, since we estimate Y_h (the leave-out spatial average) for only those combinations of region-industry where values are available for at least 5 firms (not including i), resulting in substantial data loss across the four outcomes.[50]

[49]Note that very strictly, a firm does not contemporaneously observe the political influence exerted by a competitor in this equilibrium but the most recently realized form of that influence.

[50]Some readers will note that the construction of this outcome variable is identical to somewhat popular spatial instruments. Betz et al. (2018) point out that, as an instrument, the exclusion restriction fails in cases where the independent variable of interest affects that of firms in h. In the case of political influence, here, the direct channel in Eq. 6 indicates the exclusion restriction will be violated, here by construction, and so we consider Y_h as a set of outcomes.

Table 8: Political Influence, Competition and Output among Competitors (j)

Y_h = Fewer than 20 competitors (Y=100)(Obs. 17,639)	(4)	(5)
Pol. Influence	-0.072***	-0.651
	(0.0175)	(0.395)
Constant	48.99***	49.31***
	(0.865)	(1.563)
R-squared	0.926	0.926
Marginal Effect +1 SD in Index	-0.480	-4.346
p-val.	0.000	0.111
Y_h = Total Sales (log 2009 USD)(Obs. 16,990)		
Pol. Influence	-0.007***	-0.057*
	(0.002)	(0.031)
Constant	13.29***	13.24***
	(0.057)	(0.045)
R-squared	0.947	0.948
Marginal Effect +1 SD in Index	-0.048	-0.378
p-val.	0.000	0.074
Y_h = Sales per Worker (log 2009 USD)(Obs. 16,841)		
Pol. Influence	-0.002*	-0.010
	(0.001)	(0.018)
Constant	10.40***	10.41***
	(0.0288)	(0.0289)
R-squared	0.962	0.962
Marginal Effect +1 SD in Index	-0.015	-0.065
p-val.	0.080	0.591
Y_h = Labor Costs to Sales Ratio (log)(Obs. 15,021)		
Pol. Influence	0.002***	-0.019
	(0.000)	(0.019)
Constant	-2.062***	-2.111***
	(0.025)	(0.0425)
R-squared	0.928	0.928
Marginal Effect +1 SD in Index	0.013	-0.125
p-val.	0.000	0.336
$\boldsymbol{X}$ co-variates	✓	
$\boldsymbol{X}$ interacted w/Pol. Influence		✓
Location FEs	by Sector	by Sector
Sector FEs	by Location	by Location

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$
OLS estimates. Robust standard errors, with two-way clustering at the 2-digit ISIC and region level in parentheses, per Cameron et al. (2011). Co-variates (not shown) include the log of age, the years of the manager's experience, dummy variables for exporters, foreign-owned firms, and those part of a larger firm.

These results match the specifications in Cols. 4 and 5 from Table 5. In those main specifications, we find that (relative to firm i's industry-region, an increase in Political Influence is associated with a higher likelihood of a small number of competitors, greater sales, and higher sales relative to the number of workers and a lower relative cost share of labor. When looking at the averages across competitor firms in h—that is firms in the same industry-region—by contrast, a 1 S.D. increase in firm i's influence is associated with between a 5% and 6% decrease in competitor firms' total sales, and, in the last specification, a near 2% reduction in the labor cost share ratio. None of the results for the other two outcomes is statistically significant. In fact, the results for our measure of labor productivity (sales per worker), in particular, are fairly precisely estimated but near zero, which in conjunction with the other findings, may indicate that increasing a firm's influence is associated with diverted sales, but with no correspondent reduction in labor inputs, thus raising the relative cost of that labor to overall sales.

5 Conclusion

In this paper, we set out to analyze how firms can combine several interactions with politicians and policy makers to gain influence. We apply a modified, more robust 2-PL IRT model to develop a measure of Political Influence as a latent construct; while this method itself may be unfamiliar to some readers, its close analogs in factor-type analyses are well-heeled in political science and economics literature. Specifically, our measurement model allows us to estimate influence both without a prior on how political interactions redound to influence, other than our expectation that political connections directionally lead to more influence, which is an assumption with a strong foundation. This is valuable, as the model uncovers how several of those interactions combine to result in patterns of greater or lesser influence.

Importantly, our approach allows us to calibrate a measure of influence, and to estimate its distribution. We believe this gives us the novel chance to see how political influence moves with underlying governance measures. Our findings generally support the expectations from a framework that recognizes the cost associated with political interactions. Our findings confirm what to many may be intuitive: for example, that Political Influence may be higher across the board in economies with poorer governance, as firms may find that such influence is both necessary and available. But we also uncover what we believe to be informative patterns that are new to the literature, including for instance that the spread of influence *within* an economy increases at higher levels of governance, a finding we explain by the higher cost of entry of gaining influence in environments where firms must reasonably compete with other interests, including the public's.

Lastly, though we show relationships of firm-level outcomes to provide validity to our measure, we also believe such results are revealing. We find evidence, which we believe to be robust, of relationships between greater influence and a likelihood of lower competition, increased sales, and lower labor inputs (in terms of workers or overall costs) relative to revenues. Several natural extensions of using this index to evaluate other outcomes are possible (and one outcome of this work is a publicly available firm-level data set of the index). By showing also how these relationships can vary, here by levels of governance, we also hope that our findings provide further nuance to our framework, but also justify the importance of having such a validated measure in several, diverse economies, linked to very detailed underlying data.

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A Data Appendix

A.1 Items

The table below gives the data details of the items described in Section 3.1. Unless otherwise indicated, the items are taken directly from the compiled survey data; details are also provided for composite indicators, when used. Lastly, special values (such as "Don't Know") are treated as missing, which is imputed by random forest (Wright and Zeigler, 2015).

Item/Measure		Type *(range)*
political position	Has the owner, CEO, top manager, or any of the board members of this firm ever been elected or appointed to a political position in this country?	Binary (Yes=1, No=0)
government ownership	What percentage of this firm is owned by each of the following: ... Government or State?	Continuous (0–100)
association	Is this firm part of a business membership organization, trade association, guild, chamber of commerce, or other business support group?	Binary (Yes=1, No=0)
lobbying	Referring to the most important business association that this firm is part of, how useful are the following services provided to this firm?:...Influencing regulatory decision-making processes or "lobbying"	Ordinal (Not at all useful=1, Not very useful=2, Somewhat useful=3, Very useful=4)
generalized corruption[a,b]	It is said that establishments are sometimes required to make gifts or informal payments to public officials to 'get things done' with regard to customs, taxes, licenses, regulations, services etc. On average, what percentage of total annual sales, or estimated total annual value, do establishments like this one pay in informal payments or gifts to public officials for this purpose?	Continuous (0–100)
bribery incidence[b,c]	In reference to that [application/license], was an informal gift or payment expected or requested?	Binary (Yes=1, No=0)
firm size[c]	At the end of fiscal year [Insert last complete fiscal year], how many permanent, full-time individuals worked in this establishment? Please include all employees and managers.	Continuous (5 and up)

[a] These measures are generated indicators from the Enterprise Surveys. For more information, see: https://www.enterprisesurveys.org/content/dam/enterprisesurveys/documents/Indicator-Descriptions.pdf

[b] Respondents can provide answers in either percentage terms or in local currency units; in the latter case, the data are converted into a percentage relative to given revenues.

[c] The bribery incidence indicator is measured across five transactions at different points in the full questionnaire module. These are applications for an electrical connection, a water connection, a construction permit, an import license, or an operating permit. Meetings and inspections with tax officials are also included. A single bribe incidence across those transactions is coded as Yes=1.

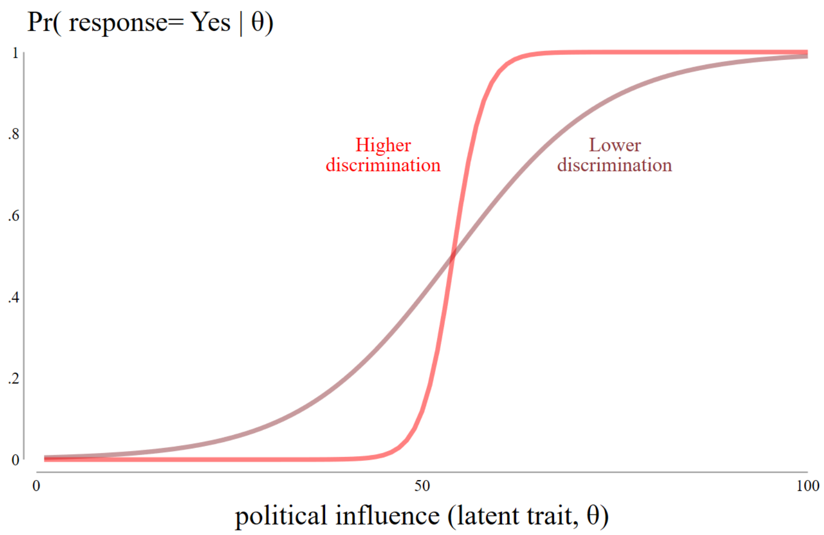
A.2 Illustation of the Estimated Parameters in an IRT 2-PL Model

IRT models have a long history of use in applications for standardized testing, where the use of IRT allows for the estimation of how well different questions on a test 'separate' test takers based along the dimension of their (unobserved) ability. Two parameters from the estimated likelihood from Eq. 7 (copied below) are worth highlighting.

$$Pr(\gamma_j, \Theta_i, \beta_j | y_{ij}) = \prod_{i=1}^{I} \prod_{j=1}^{J} g(\gamma_j \Theta_i - \beta_j)$$

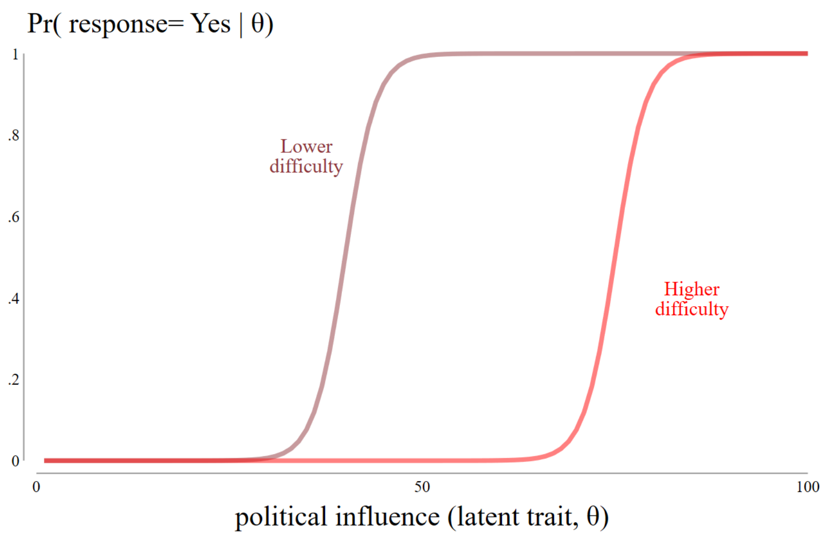
In particular, the discrimination parameter γ_j, estimates the separation of an item (like a question in a standardized test) when predicting the likelihood of an item response (a correct answer to a question), along the dimension of a latent trait (ability). Using the context of political influence, specifically, Figure A.1 shows two illustrative examples of how the likelihood of a given response (a "yes" to a question) changes as political influence increases: a higher discrimination parameter means that as influence increases, there is a much sharper change in the estimated probability.

Figure A.1: Example of Higher and Lower Discrimination Parameters



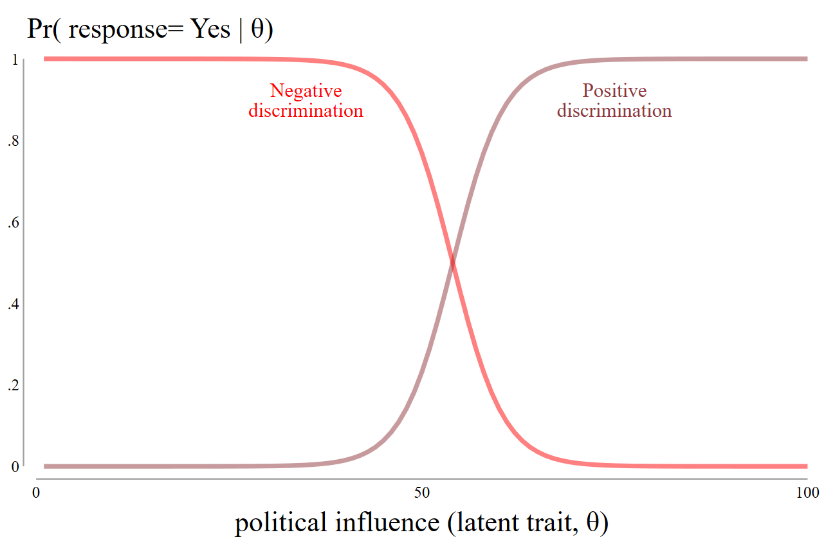
Just as well, some items may have higher discrimination, but the "answers" to those items will be more or less difficult, reflected in the 'difficulty' parameter $_j$. The example of standardized testing makes this clear: the probability of a correct answer only goes up sharply at higher levels of ability, as shown in the figure. For the exercise of measuring political influence, however, the interpretation is not as straightforward. A higher difficulty parameter on corruption could, for instance, reflect a case where only the most influential firms are able to avoid paying bribes (in the case that discrimination parameter is negative, as is the case of our results).

Figure A.2: Example of Higher and Lower Discrimination Parameters



In the case of a standardized test, it is clear that all discrimination parameters should be positive: at higher levels of ability, there should be a higher likelihood of recording a correct answer. However, in the case of determining where politicians are located on a scale of conservatism (or liberalism), it is clear that all votes should not have the same directionality. Some "yes" votes are indicative of underlying conservatism, while some "no" votes are as well. Or in the case of our items to reflect political influence, moreover, we do not have a sense a priori of what items are more indicative of political influence, and in what direction. For this reason, we do not impose a direction on discrimination parameters: they can be either positive or negative, as illustrated in Figure A.3.

Figure A.3: Example of Higher and Lower Discrimination Parameters



A.3 Sample Description

Economy	Region	Income Group	Obs.
Albania	ECA	Upper middle income	377
Armenia	ECA	Upper middle income	546
Azerbaijan	ECA	Upper middle income	225
Belarus	ECA	Upper middle income	600
Bosnia and Herzegovina	ECA	Upper middle income	362
Bulgaria	ECA	Upper middle income	772
Croatia	ECA	High income	404
Cyprus	ECA	High income	240
Czech Republic	ECA	High income	502
Egypt, Arab Rep.	MNA	Lower middle income	3075
Estonia	ECA	High income	360
Georgia	ECA	Upper middle income	581
Greece	ECA	High income	600
Hungary	ECA	High income	805
Italy	ECA	High income	760
Jordan	MNA	Upper middle income	601
Kazakhstan	ECA	Upper middle income	1446
Kosovo	ECA	Upper middle income	271
Kyrgyz Republic	ECA	Lower middle income	360
Latvia	ECA	High income	359
Lebanon	MNA	Upper middle income	532
Lithuania	ECA	High income	358
Malta	MNA	High income	242
Moldova	ECA	Lower middle income	360
Mongolia	EAP	Lower middle income	360
Montenegro	ECA	Upper middle income	150
Morocco	MNA	Lower middle income	667
North Macedonia	ECA	Upper middle income	360
Poland	ECA	High income	1369
Portugal	ECA	High income	1062
Romania	ECA	High income	814
Russian Federation	ECA	Upper middle income	1323
Serbia	ECA	Upper middle income	361
Slovak Republic	ECA	High income	429
Slovenia	ECA	High income	409
Tajikistan	ECA	Low income	352
Tunisia	MNA	Lower middle income	615
Turkey	ECA	Upper middle income	1663
Ukraine	ECA	Lower middle income	1337
Uzbekistan	ECA	Lower middle income	1239
West Bank and Gaza	MNA	Lower middle income	365

A.4 Hierarchical Co-variates

These ask respondents to rate on a Likert scale the degree of a given obstacle—no obstacle, a minor obstacle, a moderate obstacle, a major obstacle, or a very severe obstacle—poses to the operations of their firm. The included obstacles are: corruption, political instability, tax rates, the courts, and customs procedures. Likewise, in the predictors, we include several relevant firm characteristics including a firm's sector[51], a firm's export status, if it has a certain level of foreign ownership, the time its management spends on complying with regulations (the so-called 'time tax'), a firm's age, its top manager's years of experience, whether it has an internationally recognized quality certificate (such as an ISO certificate), and whether it is part of a larger conglomerate. One piece of meta data—the stratum-specific refusal rate—is included, as are a few key economy-level variables, including GDP per capita (via the World Development Indicators), a measure of potential political fractionalization (the number of seats in the legislature via Henisz (2002), updated through 2017), and lastly an electoral democracy score from Coppedge et al. (2016).

The inclusion of these co-variates allows our model to incorporate a broader array of information, including variables that are commonly available in the Enterprise Surveys data. In cases where the full set of these predictors are available, this modelling setup also allows for out-of-sample prediction, which can give an indication of latent influence even among companies from earlier waves of surveys that did not include explicit questions about political influence. However, missing data cannot be included in these hierarchical predictors, and so we use random forests (Wright and Zeigler, 2015) to predict missing values, which are generally quite low for the co-variates selected.

The tables below give the data details of the hierarchical co-variates described in Section 3.2. The data are treated the same as described in A.1. The tables are separated by thematic area but all inputted into the model. For data that are not taken directly from the ES, the source is indicated.

i) Firm Sector of Activity[a] (all binary dummies, Yes=1, No=0)	
High-tech. manufacturing	ISIC 3.1: 30, 32, 33 Examples: computing machinery, communications equipment, and medical & precision instruments.
Medium high-tech. manufacturing	ISIC 3.1: 24, 29, 31, 34, 35 Examples: chemicals, machinery & equipment, electrical machinery, motor vehicles, and transport equipment.
Medium low-tech. manufacturing	ISIC 3.1: 23, 25–28 Examples: refined petroleum products, rubber & plastics, mineral products, and metals.
Low-tech. manufacturing	ISIC 3.1: 15–22, 36, 37 Examples: food processing, leather, textiles, and wood products.
High-tech. KIS[b]	ISIC 3.1: 64, 72, 73 Examples: telecommunications, IT, and research & development.

[51] We use aggregated sectors based on categories according to technological use in either manufacturing or services sectors.

Market-oriented High-tech. KIS[c]	ISIC 3.1: 61, 62, 70, 71, 74, 65, 66, 85, 92 Examples: water transport, air transport, real estate, and machinery & equipment rentals.
Market oriented low-KIS	ISIC 3.1: 50–52, 55, 60, 63, 95–99 Examples: auto repair and sales, retail, wholesale, accommodation, land transport, and transport support.
Construction	ISIC 3.1: 45
ii) Degree of Obstacle (No, Minor, Moderate, Major, Very Severe, all converted to binary dummies)	
To what degree is [OBSTACLE] an obstacle to the current operations of this establishment?	
OBSTACLES	Tax Rates Political Instability Customs and trade regulations Courts Corruption
iii) Additional Firm-level Co-variates (range indicated below each variable)	
Exporter (0,1)	Exports make up at least 10% of a firm's annual sales
Ownership (0,1)	Firm has at least 10% foreign ownership
Time Tax (0,100)	Share of senior management's time dealing with the requirements of regulation in a typical week.
Firm age[d] (1,194)	self-explanatory
Top Manager's years of experience[d] (1,60)	Years of experience of the Top Manager in the relevant industry.
Quality certification (0,1)	Firm has an internationally recognized quality certification.
Larger firm (0,1)	A multi-establishment firm or conglomerate.

The ES data collect and classify firms according to their economic activity, using ISIC Rev. 3.1 codes. To make those codes tractable, we use more aggregated categories provided by Eurostat (see `https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an2.pdf)`. Those categories are provided in NACE 1.1; we build correspondence to ISIC Rev. 3.1 and all departures are noted in the table.

[b] Knowledge Intensive Services.

[c] This category also includes financial intermediation, insurance, healthcare, and other business activities. However, those activities are excluded from the ES population of inference.

[d] For un-bounded variables, actual range from the data is shown.

[e] Range from data shown, using re-scaled versions as they are used in the analysis.

A.5 Governance Quality Measures

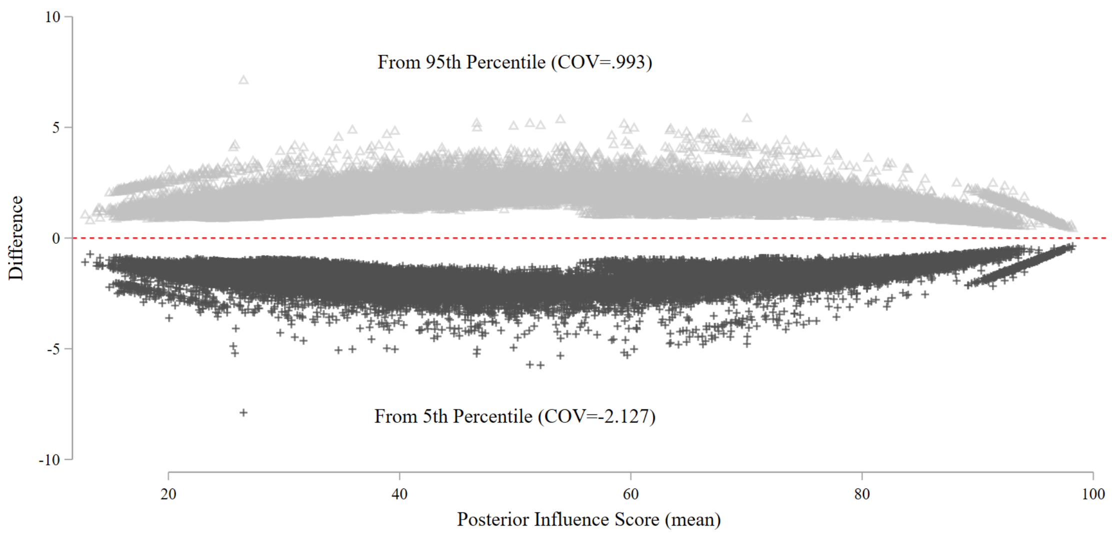
Economy-level Measures of Governance (range shown below indicator)	
Corruption Perceptions (29,79)	Corruption Perceptions Index, re-scaled so that 100 is the highest level of perceived corruption. Source: Transparency International
Political Constraints (1,60)	POLCON index Source: Henisz (2002)
Voice & Accountability (14,74)	WGI sub-component Source: World Governance Indicators
Political Stability (13,75)	WGI sub-component Source: World Governance Indicators
Government Effectiveness (28,77)	WGI sub-component Source: World Governance Indicators
Regulatory Quality (25,83)	WGI sub-component Source: World Governance Indicators
Rule of Law (23,76)	WGI sub-component Source: World Governance Indicators
Control of Corruption (23,75)	WGI sub-component Source: World Governance Indicators
Power Shift (0,1)	Takes a value of 1 if, in the last 5 years: i) There is a change in executive party in a parliamentary system ii) in a non-parliamentary system if the executive's name and party has changed. iii) in a non-parliamentary system the executive name changes and either they or incumbent is an independent. iv) is an interim government that changes. Source: authors' coding from Henisz (2002)

All data use the re-scaled indicators as used in the analysis.

A.6 Firm-level distribution of Influence Score

As discussed in Section 4.4, the estimation of firm-level political influence scores allows for a distribution of estimated posterior values. Specifically, the figure below estimates what is the difference between the mean influence score and those at the 5th (shown below the dotted, red line) and 95th percentiles (above the dotted line). As we discussed in the footnotes of that section, the expected bias (relative to the 'true', but unknown value of Θ_i) is largely driven by the co-variance between the true value of influence and this difference. Here, though Θ_i is unknown, we can provide a range of coefficient values, where (due to its positive covariance), the coefficient $\beta_{\Theta,95th}$ will be attenuated, while the negative covariance of estimates provides a coefficient $\beta_{\Theta,5th}$ farther away from 0. This gives us a range of plausible bounds for the values of β_Θ without such measurement error; put differently, by assuming different possible sizes of measurement error, we present a range of plausible coefficients.

Figure A.4: Difference between Influence Scores Measured at 5th and 95th Percentiles to Mean Posterior Score

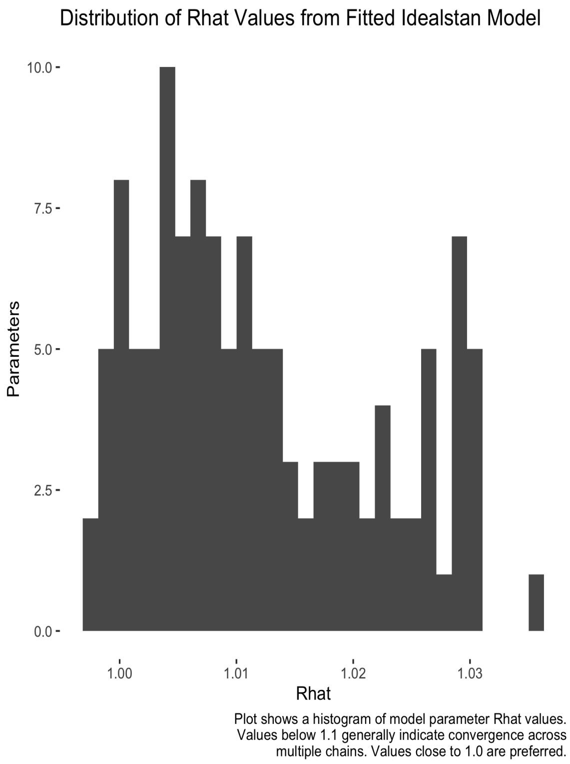


B Results Appendix

B.1 Model Convergence

A concern with many Bayesian estimation approaches is the dependence of results on researchers' choice of prior distributions. Following a procedure proposed by Gelman et al. (2013), we produce a series of split- as provided for in the Stan package developed by Carpenter et al. (2017). The split-$\hat{R}$ measure is the ratio of cross-chain to within-chain convergence, where a value of 1 indicates a stationary (converged) distribution; in other words, the model is not unstable and particularly dependent on researchers' choices of priors. It practice, split-$\hat{R}$ values below 1.1 are generally considered to indicate stable model convergence. In Figure B.1, we report the distribution of the $\hat{R}$ values. These values all are close to 1 (well below 1.1), indicating clear convergence across many chains in the MCMC process.

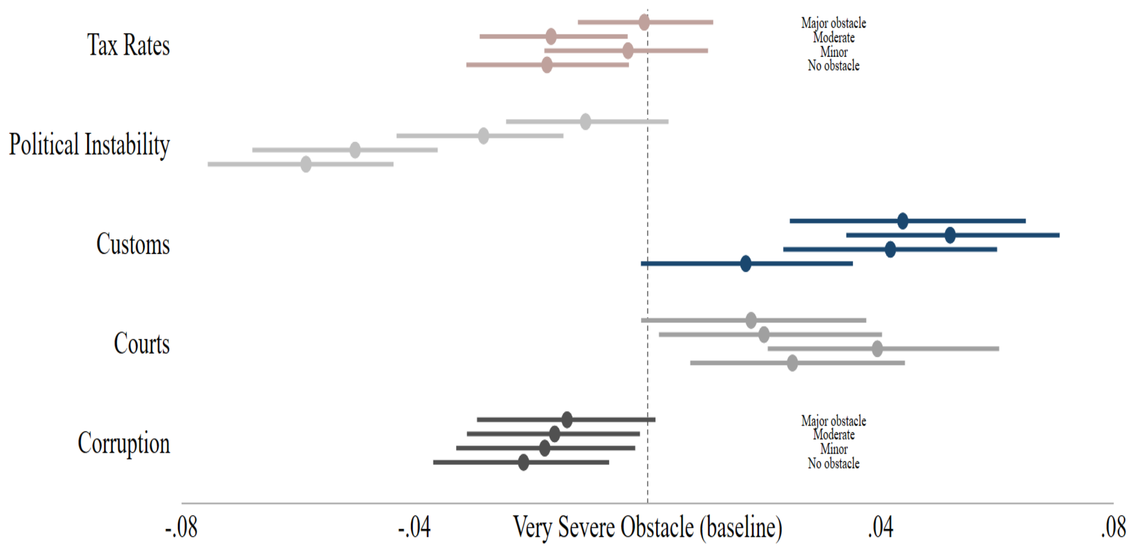
Figure B.1: Split-$\hat{R}$ Distribution



B.2 Hierarchical Co-variates

As mentioned above, our measurement model contains a first stage using the hierarchical co-variates which are detailed in Appendix A.4. For completeness, we present some of the findings from that first stage here. We start with the results shown in Figure B.2, which considers the degree to which firms rate five perception-based obstacles: tax rates, political instability, customs, the courts, and corruption. Firms rate each on a scale from “No Obstacle” to “Very Severe Obstacle”. In order to not impose any functional form (e.g., linear) on these responses, each obstacle rating is treated separately as a predictor, against a baseline rating of “Very Severe”.[52] Note also that each response cannot disentangle the myriad reasons why a respondent would give a certain rating: a rating of “Major” could indicate that a firm has had direct experience with the obstacle or that a respondent just thinks it is a problem generally. Just the same, a respondent may give a lower rating to an obstacle, even if they have such an experience, as could be the case if corruption actually helped, rather than hindered operations. For our purposes—estimating influence—separating these effects is not necessary, since we are concerned only with the predictive value of each response.

Figure B.2: Hierarchical Co-variates: Obstacles



Turning to the results, consider the response ratings shown for the obstacle posed by ‘political instability’. Though we do not impose a linear functional form, the ratings do show a sharp gradient, with a rating of “No Obstacle” predicting the least influence, ranging to the highest predicted influence at a rating of “Very Severe Obstacle”. That is, the lower a firm rates political instability as an obstacle, the less a firm is predicted to have Political Influence. On its face, this finding appears sensible as it implies that firms with more influence are also those that would find a less tenuous political environment as an

[52] This is analogous to including each discrete response as a right-hand-side variable. Note also that this approach allows us to avoid problems of scale between each of the ratings, if for instance a respondent’s idea of the difference between “Minor” and “Moderate” is not equivalent as the difference between “Moderate” and “Major”.

obstacle to their operations. Influential firms are more vested in political *stability*. A similar, but less dramatic, pattern is shown for corruption, which indicates that more influential firms are also more likely to report higher ratings for corruption as an obstacle.[53] Again, we note that a higher (or lower) rating here does not necessarily indicate that a firm has faced a request for a bribe (in fact our results from 4.1 suggest that influence displaces rents in the form of bribes). Rather, we suggest, that these ratings as predictors are an indication of how corruption is regarded poorly by firms with more influence. This finding would also be consistent with, for instance, more influential firms worrying about the general level of corruption, or even that they must leverage their influence to avoid demands for bribes, in addition to the chance that they have had a bribe demanded of them. By contrast, the coefficients on obstacle ratings for the courts suggest that firms with more political influence find these legal settings are less of an obstacle; though, again, we note that this does not imply that more influential firms necessarily use or avoid being in court any more than less influential ones. The findings on customs, show a sort of inverted-U-shaped relationship, which could be consistent with higher or lower usage rates customs by the most and least influential firms.

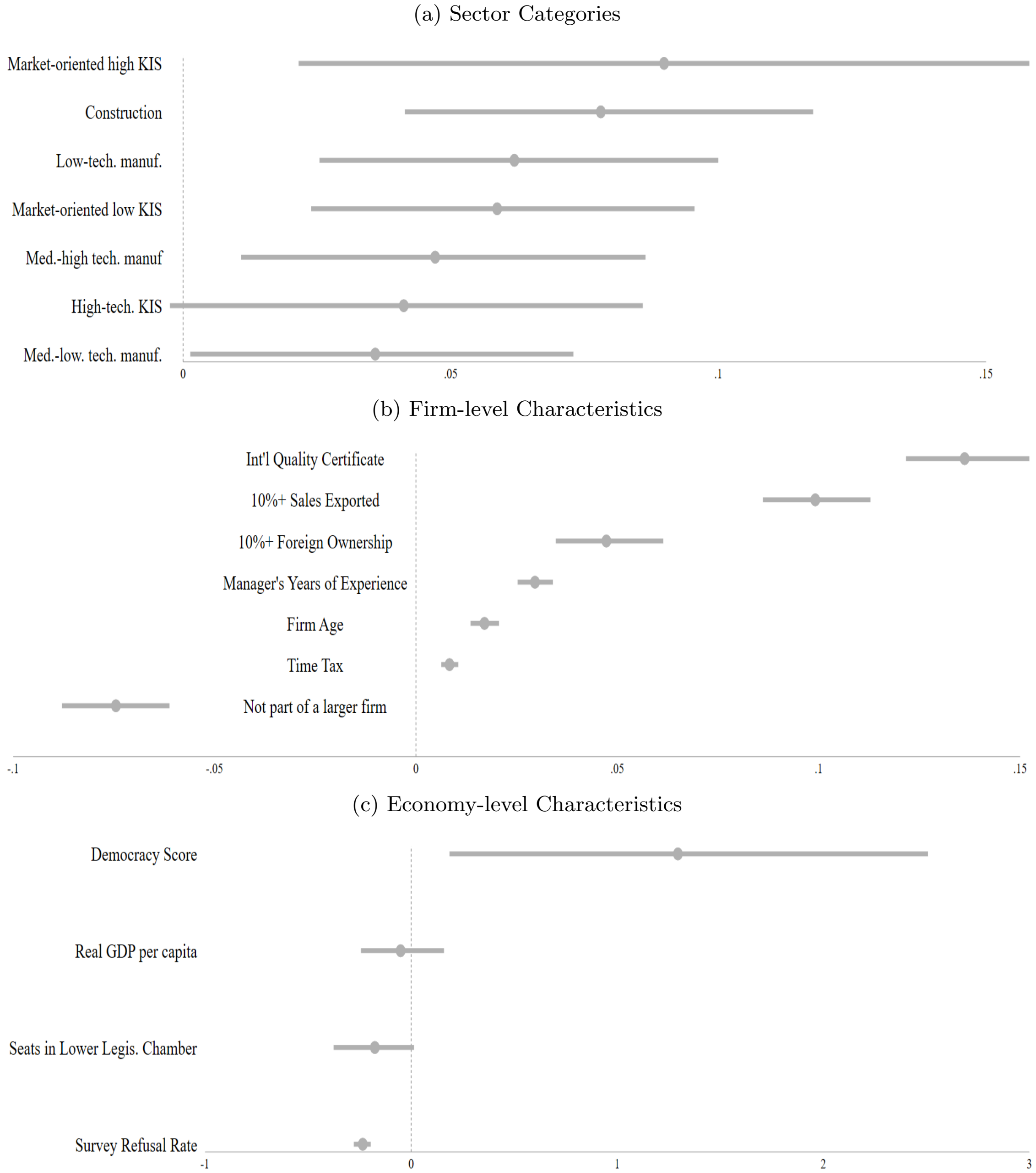
We dedicate more space here to the obstacle co-variates, as it highlights how such perception-based measures can be incorporated into a measurement model. We also consider several other potentially important co-variates, which we now turn to.[54] Figure B.3 divides these predictors into three panels, which are useful for interpretation. Panel (a) presents sector groupings, according to firms' technology intensity, separating manufacturing and services.[55] These groupings are parsimonious enough to give a generalizable understanding of Political Influence while still having enough variety and detail to serve as useful predictors. For instance, we find that market-oriented high knowledge intensive services (KIS), which include water and air transport, have the highest predicted coefficient for Political Influence (all categories are relative to the baseline of high-technology manufacturing). Market-oriented high-KIS services are followed by construction; both industry groups involve substantial state subsidies and have been discussed as captured by connected interests (e.g. in the Arab Republic of Egypt as noted in Diwan et al. (2020)). On the other end, all of the coefficients for sector are positive relative to high-tech. manufacturing (which includes industries such as computing and medical equipment), indicating that this grouping is less likely to have Political Influence.

Panel (b) features several other firm-level characteristics, generally showing that indicators of larger firm scale and international engagement (such as through exporting, foreign ownership, and age) are related to more Political Influence. We find that not being part of a larger firm, such as a multi-establishment firm or a conglomerate, reduces Political Influence, which we find as unsurprising as conglomerates can use their larger-scale operations to command greater political pressure.[56] Lastly, we include several economy-level characteristics, shown in panel (c) These show that Political Influence is

[53] To a lesser degree, we find the same pattern with tax rates.
[54] Full details on these data can be found in A.4.
[55] Using a classification based on an analysis from Eurostat.
[56] Note here we depart from calling each establishment a 'firm' *per se* to not confuse the presence of multi-establishment firms.

more likely, all else equal, in economies with greater levels of polyarchy, though it reduces with more representative legislative bodies, as proxied by the number of seats in the lower house. We return to broader indicators of governance and how they relate to Political Influence in the sections that follow.

Figure B.3: Additional Hierarchical Co-variates



(a) Sector Categories

(b) Firm-level Characteristics

(c) Economy-level Characteristics

Of course, each of these co-variates gives a hierarchical effect, *ceteris paribus*; however the resulting estimations of a Political Influence index are the result of several predictors as they exist in the equilibrium captured by our data. Though these marginal effects are useful, they do not tell us how these scores are distributed. That is, knowing that there is a positive and significant prediction of polyarchy on influence in the measurement model, does not fully examine if such economies are also characterized by business environments and firms that the model predicts will have lower influence. In the next section, we consider the resulting, estimated index scores, and analyze how those scores are distributed, including by varying several measures of governance.

B.3 Descriptive Illustration of Distributional Movements of Political Influence

This Sub-section provides descriptive results that help illustrate the intuition behind the RIF-OLS estimates in Section 4.2. The Figures below show distributions of our estimated Political Influence score. Both figures include two groups: one of lower governance quality (red dashed line), which is the quartile of economies with the poorest performance on a governance measure. For example, Figure 5 shows roughly the 10 economies with the lowest scores on the WGI Voice & Accountability measures; the red (dashed line) distribution in Figure B.4 is for the approximately 10 economies that have the highest perceived amounts of corruption according to Transparency International. By contrast, the green (solid line) distributions are those 10 economies with the highest levels of Voice & Accountability and the lowest Perceived Corruption, respectively. Each Figure also shows the 25th and 75th percentiles of each distribution (marked by the red dashed line and a solid green line).

Descriptively, then, the figures show the intuition of moving from a poorer measure of governance to a higher one, at different moments (quartiles) of the distributions. That is, in Figure 5, comparing the low-governance-quality distribution to the high-governance-quality one, shows a downward substantial shift in the 75th percentile; this shift is illustrated by the rightward line and is comparable to the coefficients illustrated in Figure 6. Likewise, the figures still show a downward shift in the 25th percentiles, but in terms of magnitude, this shift is notably smaller, again confirming the coefficient estimates in Figure 6.

Figure 5: Political Influence Distributions at High and Low Levels of Voice & Accountability

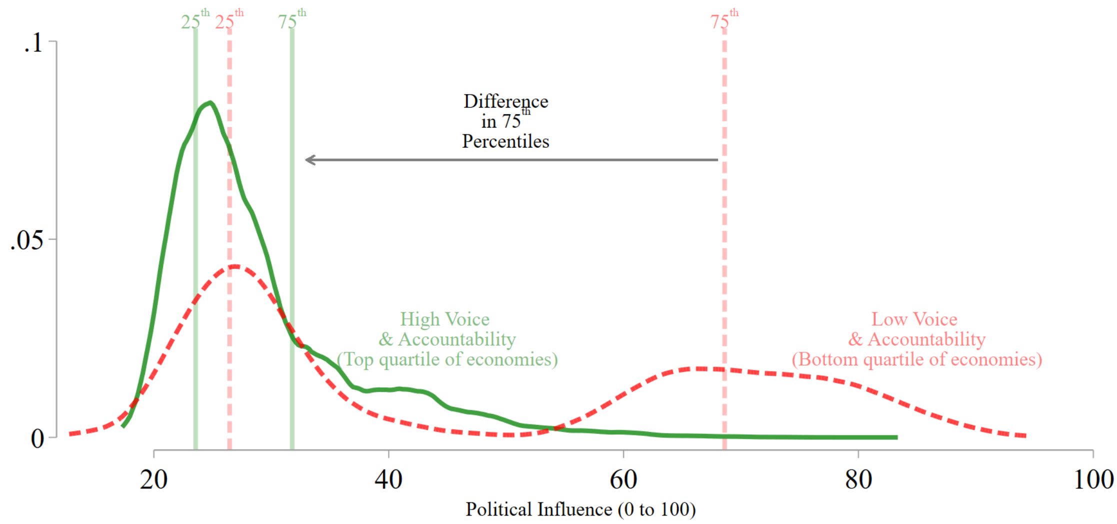
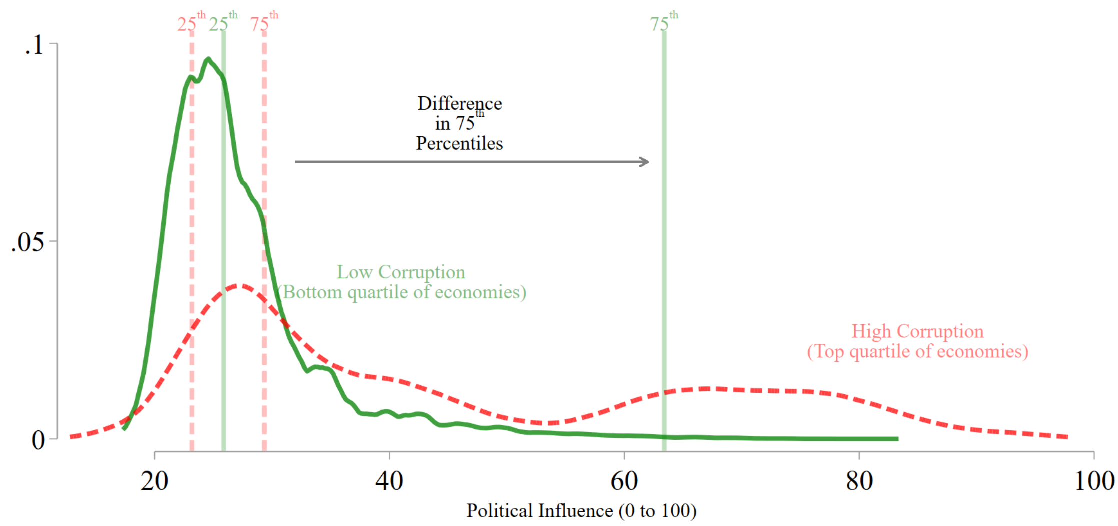
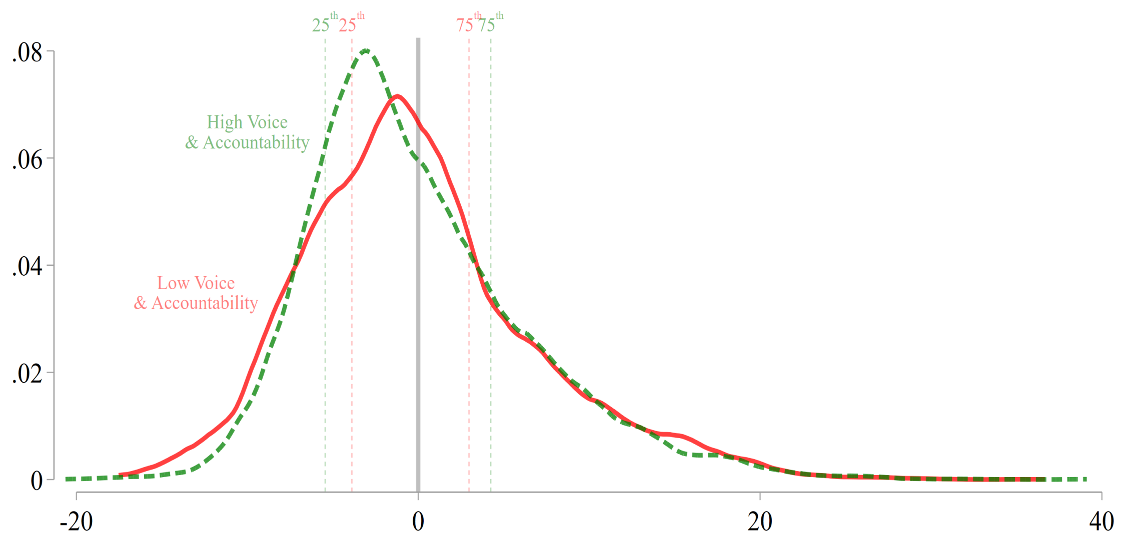


Figure B.4: Political Influence Distributions at High and Low Levels of Corruption



As we describe in the discussion around Table 4, we also run a series of RIF-OLS specifications that estimate distributions of Political Influence within economies. To do this, we re-center all Political Influence scores on their relevant, economy-level median. This is illustrated by the two distributions (again for high- and low-Voice & Accountability economy groups) in Figure B.5. The results here show the movement of both the 25th and 75th percentiles for both groups, only now they are relative to the economy-level median. This illustrates, in turn, the finding of greater dispersion of Political Influence under conditions of better governance (note that both the 25th and 75th percentiles marked by the vertical green lines are outside of the red ones).

Figure B.5: Political Influence Distributions, Centered on Medians, at High and Low Levels of Corruption

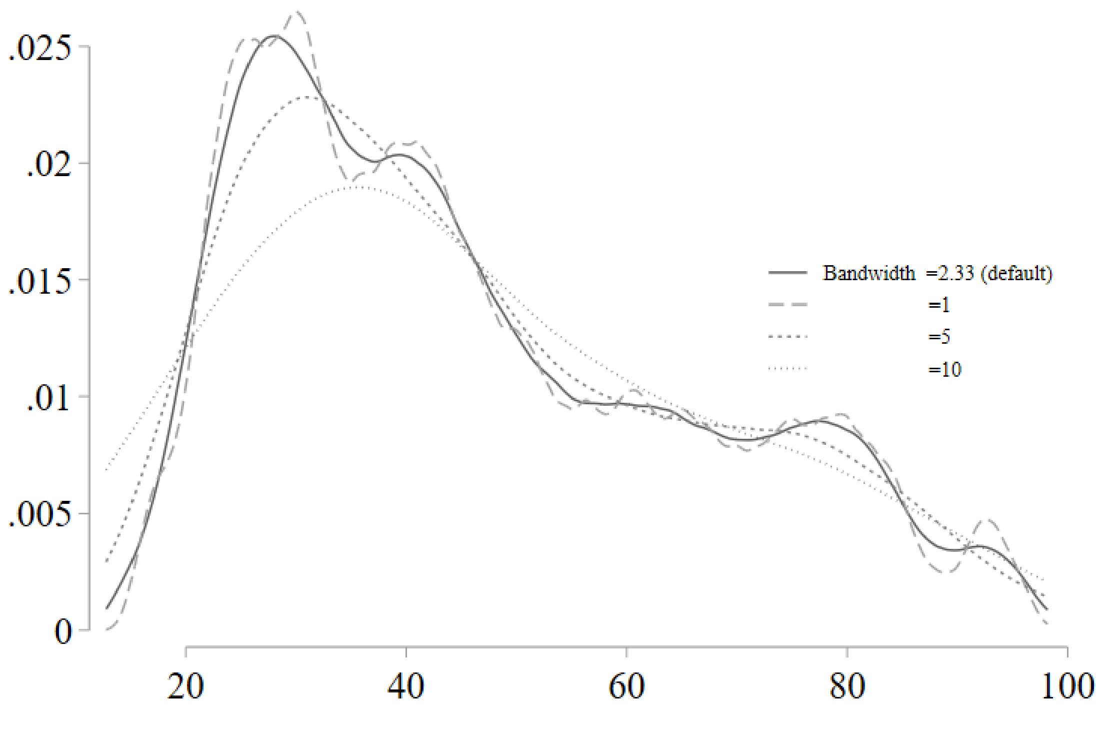


B.4 Sensitivity of Kernel Densities to Bandwidth Choice

As detailed in Porter (2015), building off the discussion from Firpo et al. (2009), since RIF-OLS relies upon the distributional some basic assumptions about the underlying distribution of the variable of interest, it will be sensitive, particularly to the choice of the optimal bandwidth in the case of using kernel densities. To our understanding (and this is the sentiment of Porter (2015) as well), the majority of those using RIF-OLS employ the default bandwidth setting in the relevant statistical software. (All RIF analyses were run using Stata v.16.1.)

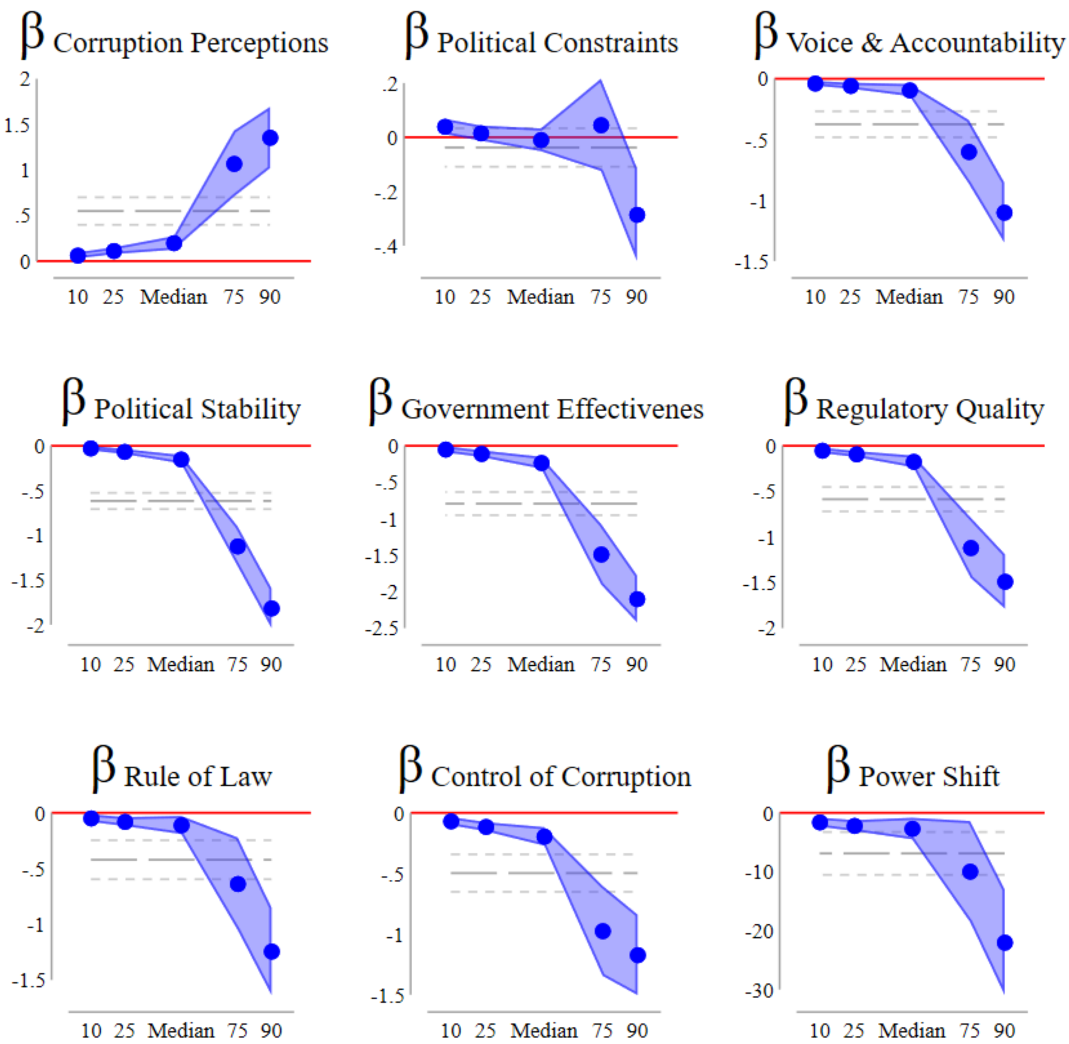
We are no different and report the default bandwidth setting in all our estimations. However, for completeness, we also provide below results of 1) the graphical kernel densities of the Political Influence score at bandwidths 1, 2.33 (the default estimate), 5, and 10. As would be expected, the lower (and finer) bandwidth allows for more mass in the distribution at the lowest levels of the Political Influence score; by contrast the broader bandwidth smooths the distribution.

Kernel Density of Political Influence, Differing Bandwidths

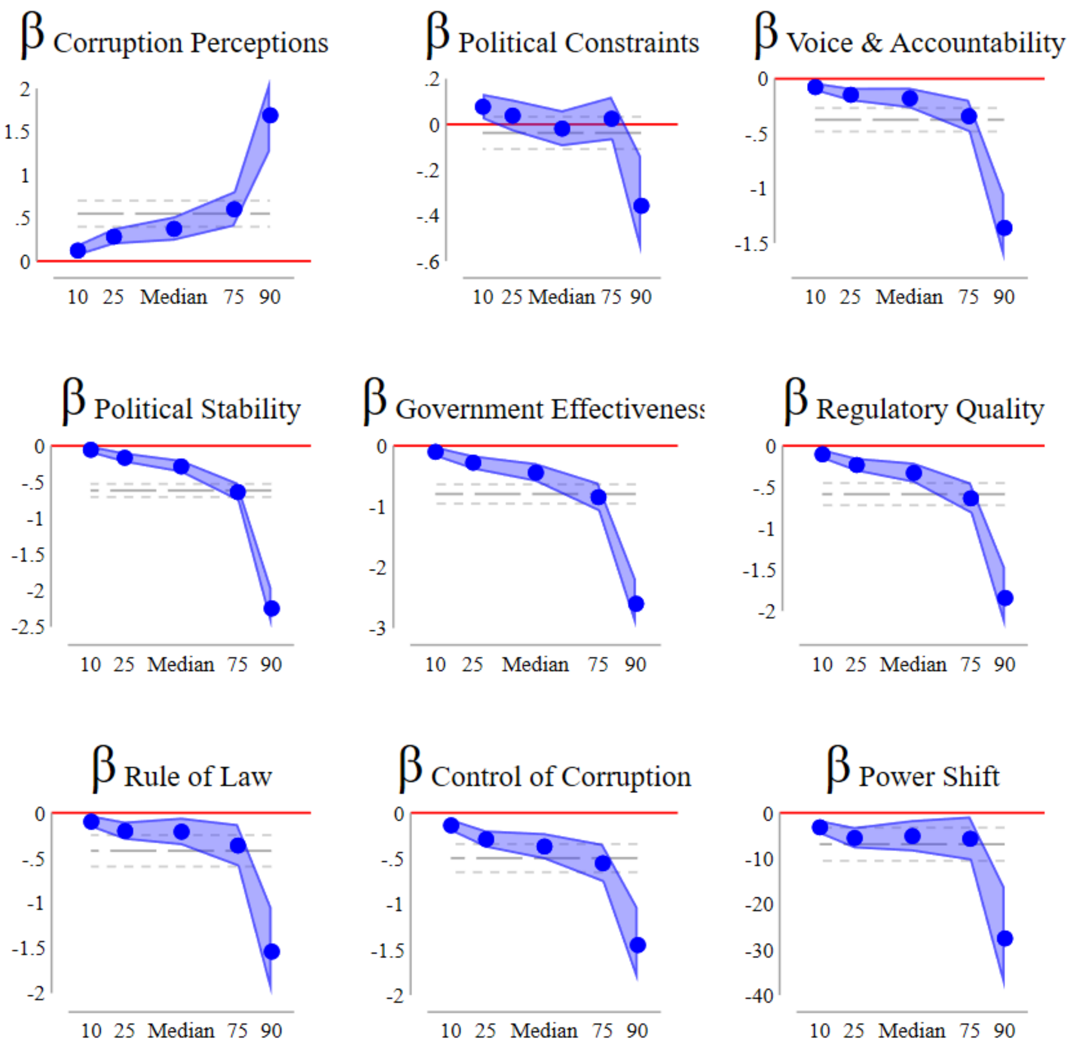


In turn, we also re-estimate the RIF-OLS results at both a bandwidth of 1 and 10 (shown in the subsequent figures). While these limits are arbitrarily chosen, they do appear to capture both a suitable range between two reasonable values of fineness and coarseness, respectively. The practical effect of this range is to broaden confidence intervals at the upper end of the distribution using a smaller bandwidth (which makes intuitive sense as the finer bandwidth reduces the effective mass at higher percentiles). The higher bandwidth value of 10, by contrast, gives more precise estimates at higher percentile values. In both figures, our results are materially unchanged with the shown 95% confidence intervals, indicating that these findings are likely not sensitive to the choice of bandwidth.

β^{OLS} and β^{RIF} at Percentiles of the Political Influence Score: Bandwidth=1



β^{OLS} and β^{RIF} at Percentiles of the Political Influence Score: Bandwidth=10



B.5 Robustness: Firm-level Outcomes by Measures of Governance

As an additional set of robustness checks to the firm-level results presented in Section 4.3, we also investigate whether the relationship of Political Influence and firm-level outcomes is heterogeneous across different measures of governance. We have reason to believe, from our initial framework that the costs of exerting political influence will vary according to underlying governance. Specifically, that where exerting political influence—at the expense of other actors, be they the public or other firms—incurs lower transactional costs, influence be more widely spread. This was borne out in the results of Section 4.2, which showed higher but more clustered levels of influence in economies with poorer governance and lower, but disperse, levels of influence in economies with higher measures of governance.

These findings invite another question, namely if firm-level outcomes also vary by underlying governance. To analyze this question, we re-take the specification provided in Eq. 12, only now we interact the various measures of governance discussed earlier (GOV_e), with the Political Influence index. This step adds the term $\beta_{\Theta,GOV} * \Theta_i GOV_e$ to Eq. 12. We also interact all firm-level co-variates in $\boldsymbol{X_i}$ by the governance measures, adding $\beta_{\boldsymbol{X},GOV} * \boldsymbol{X_i} GOV_e$.[57] We use the preferred specification in Col. 4, with industry-by-location fixed effects in all of the results presented here. While we do not attribute a causal interpretation to these results, they are reminiscent of Rajan and Zingales (1995), and are at a minimum a signal of the appropriateness of our framework laid out in Section 2.1. That is, while we cannot rule out bias from omitted variables, if we observe relationships moderated by governance quality—a proxy for the transactional cost of using influence—then it is a validating point for our measure and the results we find.

These results are best presented graphically, given the large number of coefficients. Specifically, we want to visualize how the relationship between Political Influence and any given outcome of interest may change at different levels of governance quality. To accomplish this goal, Figure B.6 plots the marginal effect between a 1 S.D. increase in Political Influence and various outcomes of interest, by holding the values of governance quality constant at various levels of the distribution of those values across 41 economies. We plot the point estimates of this relationship at the 10th, 25th, median, 75th, and 90th percentiles of each governance measure.[58] Each of these marginal effects is shown with a 95% confidence interval, which when it does not include 0, indicates statistical significance of that marginal effect, at a given level of governance quality.

However, the main result of Figure B.6 is to show how those marginal effects move as governance quality changes. Moving across these points shows a linear relationship: that is, the one given by $\beta_{\boldsymbol{X},GOV} * \boldsymbol{X_i} GOV_e$ of how Political Influence relates to key outcomes, as the quality of governance changes, say by moving from an economy with low governance quality (e.g., at the 10th percentile) to one with high governance quality (for instance, at the 90th percentile). Since the key result from Figure

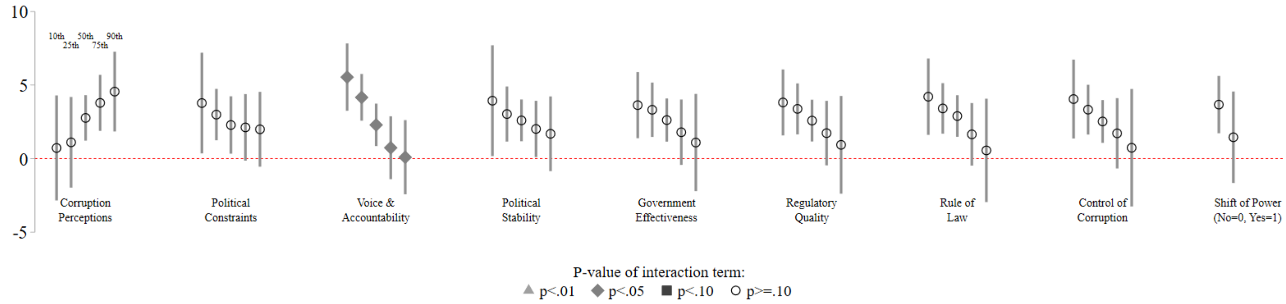
[57] Where $\boldsymbol{X_i}$ excludes relevant fixed effects at the economy and industry-by-region level.

[58] These percentiles are calculated within the sample of the 41 economies, meaning, for example, the median of a given governance measure separates half of the economies from the other half.

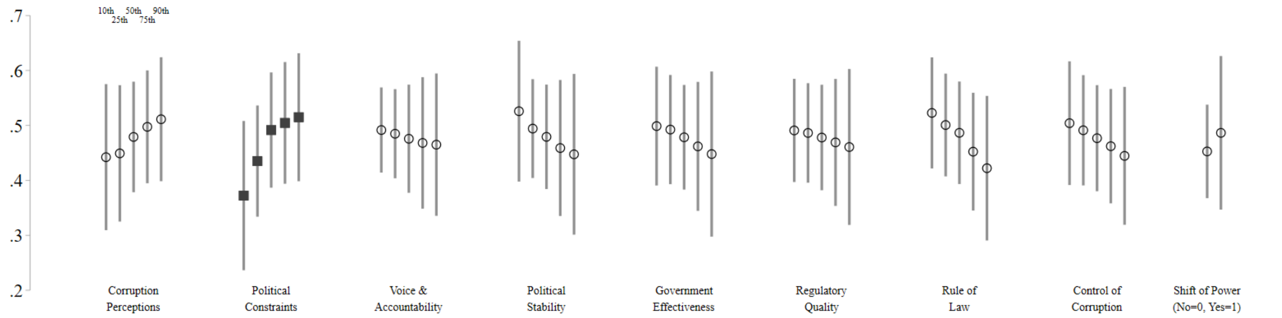
B.6 will be the slope of the linear relationship $\beta_{\boldsymbol{X},GOV} * \boldsymbol{X_i}GOV_e$, we are interested in knowing when that slope is statistically significantly different than 0. To represent this, different symbols are shown if the p-value of that coefficient is less than a given threshold (a triangle for p ¡ .01, a diamond for p ¡ .05, a square for p ¡ .1, and a hollow circle for p .1). The 95% confidence intervals for each estimated marginal effect are given by the vertical lines, with 0 shown in the horizontal, dashed red line.

Figure B.6: Marginal Effect of 1 S.D. Increase in Index, at Percentiles of Governance Measures

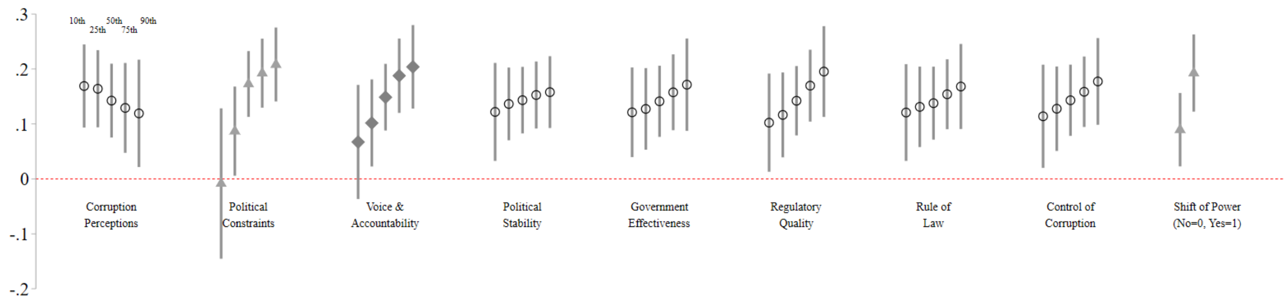
(a) Fewer than 20 Competitors (Y=100)



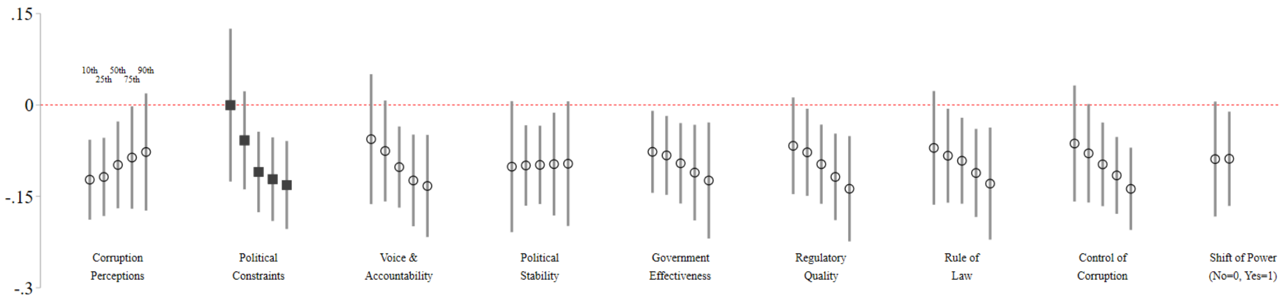
(b) Total Sales (log 2009 USD)



(c) Sales per Worker (log 2009 USD)

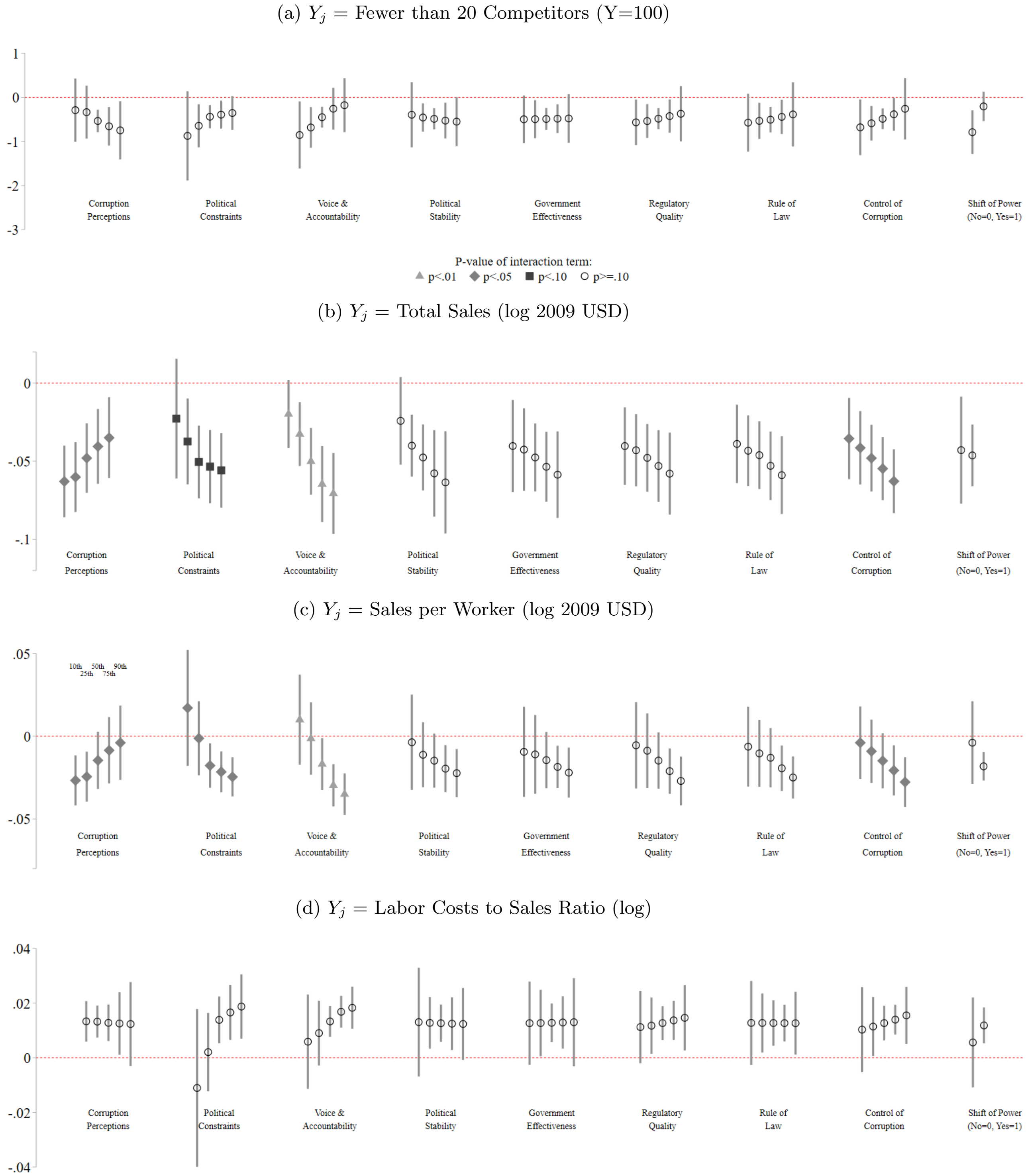


(d) Labor Costs to Sales Ratio (log)



Broadly, the interaction results do not give much suggestive evidence of a heterogeneous relationship between Political Influence and outcomes, depending on underlying governance. That is, only a handful of the interaction terms represented by the slopes of the relationships in each panel of Figure **??** are statistically significant. On one hand, even though the slopes that represent the relevant interaction terms are not significant, the point estimates for the marginal effects (with confidence intervals given by the vertical lines) lose statistical significance at different levels of governance quality. The relationship between Political Influence and our proxy for low competition (panel a, having fewer than 20 competitors), for instance, loses statistical significance at higher levels of governance quality for most measures (the slope is significant for the Voice Accountability measure). This finding could suggest that influence is associated with greater restrictions to competition when governance quality is not high. On the other hand, the relationship between Political Influence and total sales (panel b) is positive and generally highly statistically significant, regardless of the quality of underlying governance. This finding may suggest that in local contexts, it is still relative influence that matters.

Figure B.7: Marginal Effect of 1 S.D. Increase in Index, at Percentiles of Governance Measures



The results from Figure B.7 add an additional layer of nuance to our previous results. Specifically, panel a shows that where firm i has a greater level of Political Influence, its nearby firms (in h) are less likely to report that they face lower levels of competition, regardless of underlying governance. We find similar effects, that firm i's greater influence relates to its competitors' lower sales, but that this gap widens as governance improves across several of our measures (notably with lower corruption, greater political constraints, and Voice Accountability). This is consistent with a pattern where in economies with better governance, Political Influence may require a dearer cost and thus separate firms with and without influence. Similar relationships are shown for sales per worker (panel c), but not for the labor cost share (panel d).