A Dynamic Hierarchical Bayesian Measurement Model of Political Risk

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Abstract

Political risk has long been theorized as a key factor that drives the allocation of foreign direct investment (FDI). Frequently defined as the likelihood a host government will engage in actions that threaten an investor's profitability, political risk is thought to be remedied by political institutions that allow countries to make more credible commitments to honor their pre-investment promises. As a latent variable, scholars have struggled with ways to link institutions to FDI flows in the absence of a measure of political risk. This paper presents a dynamic hierarchical model of political risk that aims to address this problem by producing from observable indicators a single time-series cross-sectional measure of political risk. Additionally, this model produces estimates that allow scholars to measure within-country variation in political risk, a previously unestimated quantity. The model itself is flexible enough to be of use to comparative scholars more generally to estimate latent variables at multiple levels of a hierarchy from observable indicators produced at different levels of that hierarchy.

Many of the phenomena that interest political scientists are not directly measurable. Often, this leads political scientists to search for and employ proxy variables in order to test theories of substantive interest in the absence of direct measures. A good proxy variable should translate very directly from the concept of interest, and some concepts more readily lend themselves to good proxies. For instance, while we cannot directly measure political competition, we can do a fair job of proxying for it by measuring the margin of victory in an election, or while we cannot directly measure violence, we can measure the number of civilians killed in a conflict.

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Other concepts of interest are unfortunately less well proxied. Political risk— the likelihood a government will engage in actions ex post that threaten the profitability of foreign direct investment (FDI)– is particularly poorly-proxied. To test theories about how well domestic and international institutions alleviate political risk and increase FDI, scholars of international political economy have struggled to identify an obvious and theoretically sound proxy for political risk. An additional problem for scholars is that political risk springs from more than one source. Both national and subnational governments can pose significant threats to foreign investors, and this means that proxies at any level of government are likely to neglect significant sources of risk. To date, the literature has proposed no proxies to measure subnational political risk in a cross-national context

These two problems— a concept that is difficult to proxy and the hierarchical nature of political risk— pose serious problems for scholars interested in studying how political institutions can attract FDI by remedying political risk. In this paper, I develop a hierarchical dynamic Bayesian measurement model of political risk that aims to solve both of these problems. First, the model distills a measure of political risk from a number of indicators that are thought to be observable manifestations of that risk. This produces a measure that can be used to measure political risk in the absence of good proxies. Second, the model uses firm-level survey data from the World Enterprise Survey (WES) as observable indicators of political risk, and models them as being a function of political risk at both the national and the subnational level. This produces estimates of political risk at the subnational level, as well as at the national level. This method has the additional benefit of collapsing some of the vast trove of information available in the WES into a form that may be more accessible and useful to political scientists.

In additional, this model makes a contribution to the literature on Bayesian IRT models. Many of the contexts in which IRT models have been most common in political science— in particular, estimating ideology from the behavior of members of Congress and Supreme Court justices— are not hierarchical in nature. By contrast, many phenomena in comparative politics and international relations are the result of actions, decisions, and behaviors at multiple levels of a hierarchy, whether that means levels of government or of a national court system. This model is written to address these contexts, in which the data from which we seek to estimate an underlying latent trait are a function of multiple levels and in which we may wish to have estimates of the latent variable at multiple levels. As such, although this model is applied to foreign direct investment and political risk, it can be easily generalized to any context in which hierarchies are thought to be a relevant component of the theoretical process enerating the latent variable.

Literature

Scholars have long believed that political risk is a leading cause of underinvestment. Political risk derives from a commitment problem. Because FDI entails large sunk costs and long time horizons, multinational corporations (MNCs) are mobile prior to investing and 'stuck' afterward. This means that while potential hosts have an incentive to promise attractive terms to investors choosing between multiple locations, they cannot credibly commit ex ante to not renegotiate the terms of the investment contract ex post (Vernon, 1971). Often, we discuss this as a state-level phenomenon, and analyze how domestic or international institutions can permit countries to make more credible commitments, thus reducing political risk and attracting more FDI (Jensen, 2003; Jensen and McGillivray, 2005; Kerner, 2009; Kerner and Lawrence, 2014).

Because political risk is latent, the literature has long aimed to test theories about political risk and FDI without being able to directly measure it. Few proxy variables have been proposed to stand in for the latent variable, however. Often, because of the lack of direct measures or evident proxies for political risk, scholars have instead tested the relationship between institutions and FDI directly (Jensen, 2003; Büthe and Milner, 2008; Kerner and Lawrence, 2014). Others have chosen to use institutional variables, such as democracy or constraints on the executive, as an explicit proxy for political risk (Vadlamannati, 2012). Jensen (2006), acknowledges the threat to causal inference posed by a lack of direct measure of risk, and therefore supplements his quantitative analysis with qualitative evidence in the form of interviews. More recently, measures of risk from private agencies (Büsse and Hefeker, 2007) and political risk insurance data (Jensen, 2008; Jensen et al., 2012) have been used as measures of political risk.

The International Country Risk Guide, published by The PRS Group, one of these private agencies, provides data on many measures of political risk, although none individually are related to the risk faced by investors. Additionally, ten years of cross-national data on one indicator costs over $430. Another option is risk insurance data. Many insurance agencies, both public and private, sell insurance to MNCs investing abroad to cover their losses in the event of actions that may threaten the investment. This data, then, should provide a good proxy for political risk: insurance for investments in riskier countries should be more expensive than insurance for investments in less risky countries. The most commonly used data is from ONDD, the Belgian Export Credit Agency, as it offers risk ratings based on expropriation risk and makes its data publically available on its website (Jensen, 2008). Unfortunately, risk insurance data is also not ideal: it is proprietary and typically available only in current-year cross-sections.

One difficulty with proprietary data is that researchers do not know how the measures are constructed. This is a particular problem if the intended independent or dependent variables are implicitly or explicitly built into the measure itself. One potential flaw of expropriation risk insurance data specifically is that it is highly likely to implicitly include FDI in its construction. If this is the case, we would expect it to correlate highly for FDI, but not for theoretically relevant reasons. Consider the analogy to health insurance. As the pool of people buying health insurance expands, the expected payout of the insurer does not drop, but the cost of the payout (and thus the risk) is spread out amongst more people, lowering the cost to any individual of buying the insurance. This does not, notably, mean that the people are any healthier, just that there are more of them and the cost is spread out. In a similar vein, the more FDI that goes into a country, the less we would expect insurance on that investment to cost, regardless of the underlying risk of expropriation, because the expected cost of the existing risk is spread out. If this is true, it threatens our ability to make inferences based on the correlation between the two variables. It is also likely to rate countries that do not receive FDI for other reasons (for instance, a dearth of location-specific assets) as riskier than they may truly be. Because it is proprietary, however, we cannot know with any certainty whether this is true. Unlike some other measures in political science where we can look under the hood, as it were, to see if we consider the measure valid and reliable, proprietary data forces us to rely on trust. While to date this is the best measure that has been proposed, it is less than ideal.

An additional difficulty with existing measures of political risk is that they exist only at the national level. We can use these measures to determine which countries may have more political risk than others, but we cannot use them to test theories about within-unit variation in political risk. Extant research lays plain that we cannot expect that threats to investors occur only at the national level or are uniformly geographically distributed throughout a country. Although the addition of layers of government could be thought to stabilize policy, reducing the risk of ex post policy shifts and therefore decreasing politial risk (Henisz, 2000; Jensen and McGillivray, 2005), there are many actions subnational actors can engage in that would threaten investment— chiefly, subnational officials are cited as being engaged in corruption, but also delaying or denying permits, halting production, and blocking access roads (Lewis, 2005; Bardhan and Mookherjee, 2006; Fan, Lin and Treisman, 2009). Increases in FDI may also increase a subnational government's power vis-a-vis the central government (Malesky, 2008), suggesting not only that political risk and FDI flows vary within a country, but also that they are politically important. The existence of FDI and presence of multinational corporations at the subnational level may theoretically provide local governments with targets for behaviors they would not have engaged in beforehand, suggesting that the link between political risk and FDI may actually potentially be reversed at the subnational level. Because subnational officials can engage in behavior that would increase political risk, and because there is substantial within-country variation in other relevant indicators, we should expect to see within-country variation in political risk, and measures of this variation would be valuable for researchers.

In this paper, I present a more transparent, longitudinal measure of political risk, as well as a broadly applicable model to estimate latent variables in hierarchical contexts. This paper leverages two key features of Bayesian measurement models to produce both national and subnational estimates of political risk. The first feature is that this class of models allows us to estimate a latent trait using data available on observable variables we believe to be manifestations of that trait. This is useful because political risk is not directly measurable, but actions thought to be generated by political risk, like expropriation and acts tantamount to it, are. Thus, unlike existing measures, this is a measure based on behavior rather than on perceptions. What is more, data on these manifestations are available at both the national and subnational levels and for a wide variety of countries and years, meaning that this type of model can estimate a theoretically-appropriate and time-varying measure for political risk at multiple levels of government.

The second feature of Bayesian measurement models is that they permit the researcher to collapse into one dimensions a trove of data that may be valuable but unwieldly and difficult to use. A key example of this are roll call votes in the United States Congress– while these provide valuable information about ideology and other characteristics of legislators thought to be relevant to their voting behavior, a list of roll call votes in itself is not terribly useful to researchers. When used a indicators in an IRT model, however, researchers can derive from this store of information a measure of ideology that can be useful to them in testing theories about ideology. In the context of political risk, the World Enterprise Survey provides tens of thousands of firm-level responses to questions that are theoretically linked to political risk, but are neither direct measures of political risk, nor are, in their raw form, particularly easy to use for social science purposes. In this model, I derive from these questions a single estimate of political risk.

Indicators

Bayesian measurement models, or item response theory (IRT) models, are used to estimate latent variables thought to be present to some degree in all observations within the data. They operate by taking in a selection of indicators believed to be driven by the underlying trait, and using them to estimate both that underlying trait as well as some features of each indicator. Some use as indicators the measures others have generated of the underlying variable, in which case the translation between indicator and underlying variable is clear— they are the same (Pemstein, Meserve and Melton, 2010; Linzer and Staton, 2014). Others use behavioral data, such as votes, as their indicators to estimate one (Martin and Quinn, 2002) or many (Lauderdale and Clark, 2012) dimensions of underlying latent behavior. In either case, it is of paramount importance that the indicators included in the model have strong theoretical ties to the underlying variable one hopes to estimate. In this model, I use firm responses to questions relating to government behavior toward business, a function of both subnational and national political risk, as well as national-level behaviors that theory and definitons would lead us to expect in especially risky countries.

The World Enterprise Survey (WES) is a yearly survey of representative firms within countries on a variety of topics. The survey is conducted in a sample of countries every year, but is not conducted in each country in every year. For the purposes of estimating the underlying political risk, I chose the five questions from the survey that most closely relate to potential government interference in business. The total sample covers 122 developing countries for the years 2006-2013[1].

The questions from the survey that serve as indicators are the following. All are dichotomous or ordinal variables.

[1] For a table of which years cover which countries, and the number of surveys conducted in each, see Appendix C.

- Agree or disagree: The courts are fair. (1-strongly disagree, 4-strongly agree)
- Agree or disagree: The government's interpretation of laws and regulations pertaining to the establishment are consistent and predictable. (1-strongly disagree,4-strongly agree).
- Are gifts expected for tax collectors? (Yes or no)
- Is corruption an obstacle? (0-no obstacle,4-very severe obstacle)
- Are licenses and permits required? (0-no, 4-very severe)

Importantly, this survey records not only the country, but also the region within the country in which the surveyed firms operate. This allows us a rare look into subnational variation in a country's investment climate. We would expect that a region in which firms consistently say that the courts are fair, the government is consistent and predictable, gifts are not expected for tax collectors, corruption is no obstacle, and few licenses or permits are required exhibit less political risk than regions in which firms say the opposite is true. As such, all indicators are oriented such that higher values of the indicator correspond with higher expected values of risk. In total, there are 464 regions represented in the data. What constitutes a 'region' varies by countries— in some they are cities, in others administrative units, and in yet others states. For a few countries, such as Russia, the unit of analysis shifts between survey-years from one subnational level to another, but for most the units remain the same across survey-years. Because this is supposed to be a representative survey of firms operating within the country, not all regions are always represented in a survey. Omitted regions should be the regions with the fewest firms operating within them. Including these would likely produce biased results, as regions without firms operating within their borders may not exhibit risky behavior simply because of lack of opportunity.

One could reasonably counter these measures by arguing that gifts for tax collectors and corruption as an obstacle are not reasonable indicators of political risk as defined here. Certainly, these two are much stronger measures of corruption than they are of political risk. Any indicators that are not purported to be direct measures of a latent variable are likely to have noisy data generating processes— that is, there are a number of factors that contribute to the manifestation of any one indicator. What matters for the purposes stated here is that each indicator is a theoretically-driven manifestation of the latent concept, and that only one dimension drives all the indicators. When combined with the other three measures, I argue that the common element uniting all five is political risk. Corruption is not expected to constitute a second dimension— perceptions of court fairness could be weakly driven by corruption, but I argue that increased corruption would not be a driver of a less consistent and predictable government or of more licenses and permits being required. Thus, I argue that the latent dimension underlying these five measures is political risk. From these indicators, the model will produce not only estimates of national and subnational political risk, but also a parameter that indicates how well-correlated each indicator is with the underlying latent variable. We can use those parameters to revisit our assumptions of how strongly, if at all, each of these is an indicator of political risk.

At the national level, I use three observable indicators. Typically, political risk is defined as the likelihood that a government will renegotiate the terms of the initial contract in a way that threatens an investor's profitability, although more broadly it tends to apply to any ex post action by a government that threatens the investor. Observable manifestations of this at the country level would include acts of expropriation and shifts in policies that affect investors, such as tax rates.

The first indicator is a count of the number of bilateral investment treaty (*BITs*) disputes that are brought against the country in a given year, as compiled and arbitrated by the International Centre for the Settlement of Investment Disputes (ICSID). BITs are agreements signed between a dyad of countries, typically a developed country and a developing country, that assure a set of rights for investors and provide for an international tribunal in which foreign investors from either signatory country can take legal action against the other signatory country if they believe its rights have been violated. Arbitrating a BIT can be costly and time-consuming, and as such, these disputes are typically not filed lightly. Having a BIT dispute filed against a country is therefore a relatively clear indication that the country is engaging in activities that may be violating the profitability of investors, and may thus be more politically risky.

The original distribution of this variable ranges from 0 to 10 for any country-year, with the maximum number of cases being brought against Venezuela in 2011. For 86% of country-years, however, no BITs disputes were brought. Only 1.1% of observations had three or more BITs disputes in a country-year. As such, for the ease of modeling this as a categorical variable rather than a count variable, I collapse this into four categories: none, one, two, and three or more BITs disputes filed in a country-year.

The second indicator, *exprop*, is a count of expropriations involving divestment of Foreign Direct Investments (FDI) from Hazler (2012). Expropriation is the act of a country nationalizing or otherwise taking possession of a firm's assets, and it is the clearest manifestation of political risk. While actually engaging in an expropriation is indicative of very high political risk in a given country year, it is not necessarily the case that not engaging in expropriation is indicative of very low political risk. In this way, expropriation may be a misleading indicator. For future versions of this model, I want to collect data on the number of legislative acts proposed or discussed that pertain to expropriatory acts in a given country-year, which will be a much more nuanced and accurate measure of political risk[2].

Similar to BITs disputes, for the ease of modeling, I collapse this variable into three categories: none, one, and two or more expropriations in a given country-year. Ninety-nine point three percent of countries years have no expropriations reported in the data. The most reported is five expropriations, which occurred in Bolivia in 2006. The second highest number of expropriations in a given country-year is 2 in Ecuador in 2006.

The third indicator (taxchange) is a measure of the absolute value of the change in a country's reported corporate tax rate from year t to year $t + 1$. The data on reported corporate tax rates are taken from the World Bank's Ease of Doing Business index. If an investor enters a country when it has a certain tax rate, but the tax rate is prone to fluctuations, this may be an observable indicator that the country is engaging in behaviors that change the terms of the initial contract and threaten investor profitability[3]. In contrast to using the actual tax rate in any given year, which may threaten an investor's profit margins but can also be accounted for if known beforehand, using the year-on-year change instead gets at both the element of profit threat as well as unpredictability and a change in the terms of the initial contract.

In its raw form, this variable ranges from no change from the previous year (41% of observations) to 202.8% change from the previous year (Sierra Leone in 2012). Only seven country-years experience a change from the previous year of greater than 50% (Burundi 2011, Burundi 2012, Sierra Leone 2012, Yemen 2007, CAR 2007, CAR 2012, and Sri Lanka 2013), and 72% of country-years have a change of less than 4%. To account for the high number of zeros and extreme right skew in the distribution of this data, and for the ease of modeling, I ordinalize this variable based

[2]The estimates are not changed substantially by excluding the expropriation variable, as demonstrated in Appendix A.

[3]This is true regardless of the reason the country changes the corporate tax rate. It is also the case that countries often actually do not charge firms the stated tax rate, yet it remains true that a fluctuating tax rate may indicate underlying political risk.

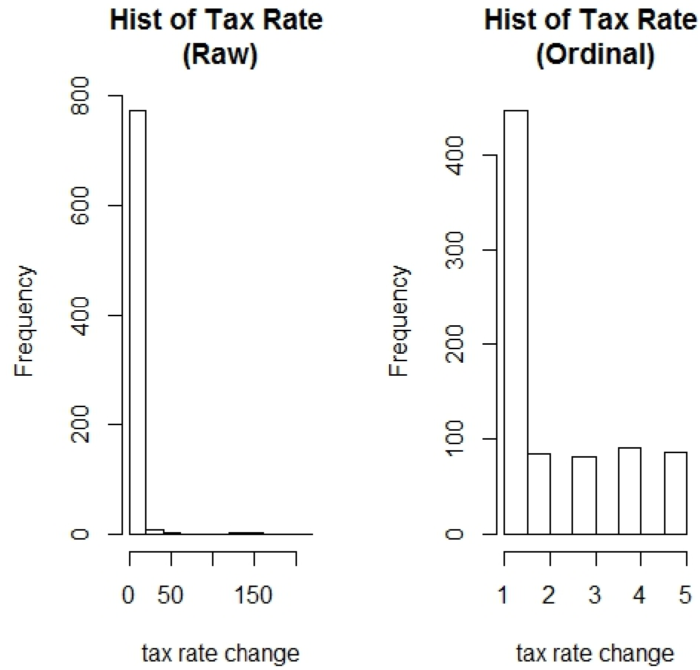

Figure 1: Raw and ordinalized distributions of tax rate change.

original	ordinal	frequency
$0< x <.2$	1	447
$.2\leq x < .6$	2	85
$.6 \leq x < 1.7$	3	81
$1.7 \leq x < 3.95$	4	91
$3.95 \leq x \leq 202.7$	5	87

Table 1: Criteria for ordinalizing change in tax rate.

on quantiles, according to the criteria in Table 1, producing a distribution of data that looks like Figure 1 (right).

Notably, there are two variables I do not use as indicators although they are likely to be indictive of political risk: democracy and FDI. Democracy is thought by many to help ameliorate political risk, and widely regarded as why democracies receive more FDI on average than do non-democracies. Democracy is also used by some as a proxy for political risk, for this reason. I do not include it as an indicator because including democracy in the measure itself would preclude us from using this measure of political risk to test theories about democracy and political risk. Similarly, if theory is correct, FDI is almost certainly an observable manifestation of political risk. That is, after all, the entire reason we study political risk. However, using FDI as a component of this measure of political risk would not allow us to test to see how the measure is related to FDI, because we would be assuming the relationship in the construction of the variable.

One might reasonably ask why, if these are indeed indicators of a country's political risk, they cannot individually or jointly be used as proxy variables. One reason is that these types of manifestations, although representing 'a catastrophic event for investors' (in the case of expropriation) and quite clearly part of their decision-making, are very rare (Jensen, Malesky and Weymouth, 2014). In survey results reported by Jensen et al, only nine percent of investors reported nationalization-related losses in the previous three years. In the data I use, expropriations are similarly rare, as are BITs disputes, and significant tax rate changes. As such, and because they each only capture a portion of the overall concept of political risk, these are not individually useful as proxy variables.

Methodology

Bayesian IRT models function by selecting a series of observable variables that are all thought to be driven by the same underlying trait and then estimating from them that underlying latent trait. We do not have to believe that this underlying trait is the *only* factor driving these observable manifestations, as long as it is *a* driving factor behind their occurance. It uses these observable indicators, y_i, to estimate right-hand-side variables that provide information both about the indicator and about the actor engaging in the behavior.

In this case, the model takes in a matrix of indicators that occur on the country level and a matrix of indicator that occur at the subnational level. The primary source of data are firm-level responses to questions on the World Enterprise Survey. As these firms are located within subnational units, and these subnational units are themselves located within countries, a hierarchical IRT model is proper to tease out the underlying factor, political risk, driving these behaviors. In plain language, we believe that the firms' observations about the government are indicators of the government's political risk, and that this risk is comprised of both subnational and national components. Additionally, in this model I assume that the risk posed by subnational governments relative to that posed by national governments is greater in more decentralized countries than in less decentralized countries.

Assume, then, that we have N firms operating in R regions in C countries, and that they are surveyed for t years. Each firm provides answers to M relevant questions, each of which have K possible responses. The probability that a firm gives a response $k \in 1, 2...K$ on question $m \in 1, 2...M$ is a function of features of both the question m as well as features of the region r and country c in which the firm is operating. The region r and country c both have underlying, latent political risk, that is time variant and that drives them to behave as they do, denoted x_{rt} and x_{ct}[4]. Additionally, let us use data on one measure of decentralization, the proportion of spending done on averge by subnational governments in a country[5], (d), as a weight on the region's political risk, and the proportion of spending done by the national government $(1 - d)$ as a weight on the nation's political risk[6]. This suggests that, in more decentralized countries, the subnational government's political risk is a stronger driver of a firm's response to the survey questions than in less decentralized countries.

There are two relevant features of the question m: its discrimination parameter, β_m, and a series of cutpoints that divide up the propensity score space into k responses. The discrimination parameter provides information on which indicators or questions are most highly correlated with the underlying latent parameter. The cutpoints divide up the response space into categories and indicate how 'difficult' it is to attain a given level of that indicator.

Let τ_k denote a series of cutpoints, such that $k = 1, 2...K$, where, K, again, is the total number of possible responses to question m. Let us further specify that $\tau_1 < \tau_2 < ...\tau_K$, and $\tau_1 = -\infty$ and $\tau_K = \infty$ (King, 1989)— that is, the cutpoints are in sequential order (a response of 1 is not higher than a response of 2, for instance), and they span the entire space. Given these specifications, the ordered logit link function specifies that the probability a firm i gives answer k to question m in year t is:

[4]For countries with only one region represented in the data, I estimate both survey and national-level indicators as functions solely of a national-level political risk. I do not estimate regional political risk for these countries. While subnational political risk is almost certainly not absent in these countries, with only one unit it is difficult to distinguish the subnational risk from the national risk. Additionally, countries with regional names that do not correspond to actual regions— for instance, "Rest of the Country"— are coded as having only one region and omitted from regional estimates. Although I lose within-country variation by doing this, it is unclear how valuable a risk estimate for these non-regions would be.

[5]From the IMF's decentralization indicators.

[6]This measure exhibits significant missingness. Where a country had at least one year with a non-missing value, I use that data to fill in the gaps. Where all years are missing, I assign that country-year the average value for all countries with data in that year.

$$Pr(y_{imt} = k) = logit^{-1}\beta_m(\tau_{mk} - (dx_{rt} + (1-d)x_{ct})) - logit^{-1}\beta_m(\tau_{m(k-1)} - (dx_{rt} + (1-d)x_{ct})) \quad (1)$$

The subnational government's level of political risk, x_r, captures the temporal element by being modeled as a random walk, with each region-year's risk modeled as being distributed normally with a mean at the prior year's risk estimate and a set standard deviation (Martin and Quinn, 2002). The first year for each region-year is also distributed normally, centered at zero with a set standard deviation. This accounts for our theoretical belief that underlying political risk can change over time, but that it is related to past levels of political risk. Here, I assume that risk is normally distributed within this sample of regions within developing countries, with very few regions exhibiting very high or very low levels of political risk, and so I assign it a normal prior. This runs somewhat counter to the distribution we see in the political risk data, where the distribution appears to be mixture of an approximately normal distribution along with a distribution with a large portion of ones, but seems rational. The resulting estimates are robust to changing the normal prior to a uniform prior (see Appendix B).

$$x_{rt} \sim \mathcal{N}(x_{r(t-1)}, \sigma^2) \text{ and } x_{r1} \sim \mathcal{N}(0, \sigma^2) \quad (2)$$

This is one way of linking the two levels of the hierarchy, and produces estimates of risk that are properly interpreted as the amount of risk relative to the country, as will be discussed in more detail in the following sections. How one chooses to link the levels of the hierarchy largely hinges on the modeler's beliefs and assumptions about the data-generating process. In this case, because the firms in the survey are clearly subject to two governments, and the questions are not specific as to governmental actors, it is a reasonable modeling choice to assume the responses are a function of both national and subnational political risk. To account for deree of decentralization, the region's risk and the national level risk are both weighted by their proportion of total average spending in a country. The model then effectively 'nets out' the commonality between the districts, which is the national element, and reserves the rest to the subunits. In the case in which there is a set of obviously subnational and obviously national manifestations, one might instead choose to link the levels using an approach similar to random effects, by modeling the subnational indicators as a function of subnational political risk, and have the subnational political risk be drawn from a distribution with mean at the national political risk. For the data I use here, I prefer the former approach so as to not make assumptions about which level of government is engaging with the firm. The results should be substantively similar, although the interpretation, as will be discussed later, may be slightly different.

The country's political risk, x_{ci}, is modeled as one component in the theoretical process generating the survey data. In addition, I use data on additional manifestations of political risk that occur only at the national level. The equation I estimate for this component is the same as that in Equation 1, except that the probability of firm i gives answer k to question m in year t is a function of only the country's political risk, rather than both the country's and region's levels of political risk.

$$Pr(y_{imt} = k) = logit^{-1}\beta_m(\tau_{mk} - x_{ct}) - logit^{-1}\beta_m(\tau_{m(k-1)} - x_{ct}) \tag{3}$$

Similar to the regional risk estimate, a country's level of political risk in year t, x_{ct}, is drawn from a normal distribution with mean equal to the country's political risk in year $t-1$, and with a set standard deviation. Each country's political risk in year 1 is drawn from a standard normal distribution. For both this and the subnational political risk, estimates can be made from pooled data by simply modeling the distributions as centered at 0 instead of at the (non-existant) previous year's mean. For certain applications, the pooled approach may be more sensible, even with longitudinal indicators, as the following sections discuss.

$$x_{ct} \sim \mathcal{N}(x_{c(t-1)}, \sigma^2) \text{ and } x_{c1} \sim \mathcal{N}(0, \sigma^2) \tag{4}$$

To aid in convergence, I use the insurance risk data from Jensen (2008) as initial values for a country's risk in each country-year, standardized to have mean 0 and standard deviation 1. I choose to use these as initial values, but not include them in the model because they either aid in convergence by starting each chain in roughly the position we expect relative to other countries, or, if the data disagree with that ordering, the chains can quickly and easily move away from them if they prove uninformative. In this sense, we can then incorporate this proprietary data as priors but not rely upon it heavily. For countries not included in Jensen's (2008) data, the initial values are random draws from a standard normal distribution. All other variables have diffuse normal priors and randomly generated initial values.

Cross-Sectional Estimates

Because the surveys that make up the vast majority of the data are not done in each survey in each year, a sensible starting approach is to pool all of the surveys to determine one over-arching level of political risk for the entire time period. With the model run on the pooled sample, it produces much more precise estimates of political risk, but at the expense of a time-invariant (and thus possibly, for any given year, incorrect) measure.

This model produces four results of interest and use to the researcher. First, it allows for a relative ranking of countries on the dimension of political risk (Figure 2). This produces estimates of political risk that can be interpreted in relative terms rather than absolute terms. That is, it is not the case that a country with a risk score of 0 is not risky, that negative scores have negative risk, and positive scores have positive risk, nor is it the case that a risk score of 2 has twice as much political risk as a score of 1. We can say that a country with a higher risk score is riskier than one with a lower risk score. A second point is that each estimate is accompanied by a ninety-five percent credible interval— the range spanning ninety-five percent of the posterior distribution of the estimates— and this stated uncertainty means that countries with overlapping CIs are of comparable levels of risk, even if one is ranked higher than another. This means that in Figure 2, we can say definitively that countries in the right panel are riskier than those in the left panel, and that Brazil, Yemen, Ecuador, and Chad pose more risk to investors than do the Slovak Republic, Antigua and Barbuda, Lesotho, and Siera Leone. Overlapping credible intervals do mean, however, that we cannot say which of the Yemen, Ecuador, and Chad are the riskiest. This is less an empirical shortfall than a reflection of reality: it seems likely that many countries are so similiar in their political risk profiles as to be nearly indifferentiable.

The results of this model also allows researchers to see a comparison of subnational units cross-nationally (Figure 3). In total, there are 464 unique subnational units in the sample. Because the model is written to accommodate both subnational and national-level political risk for the

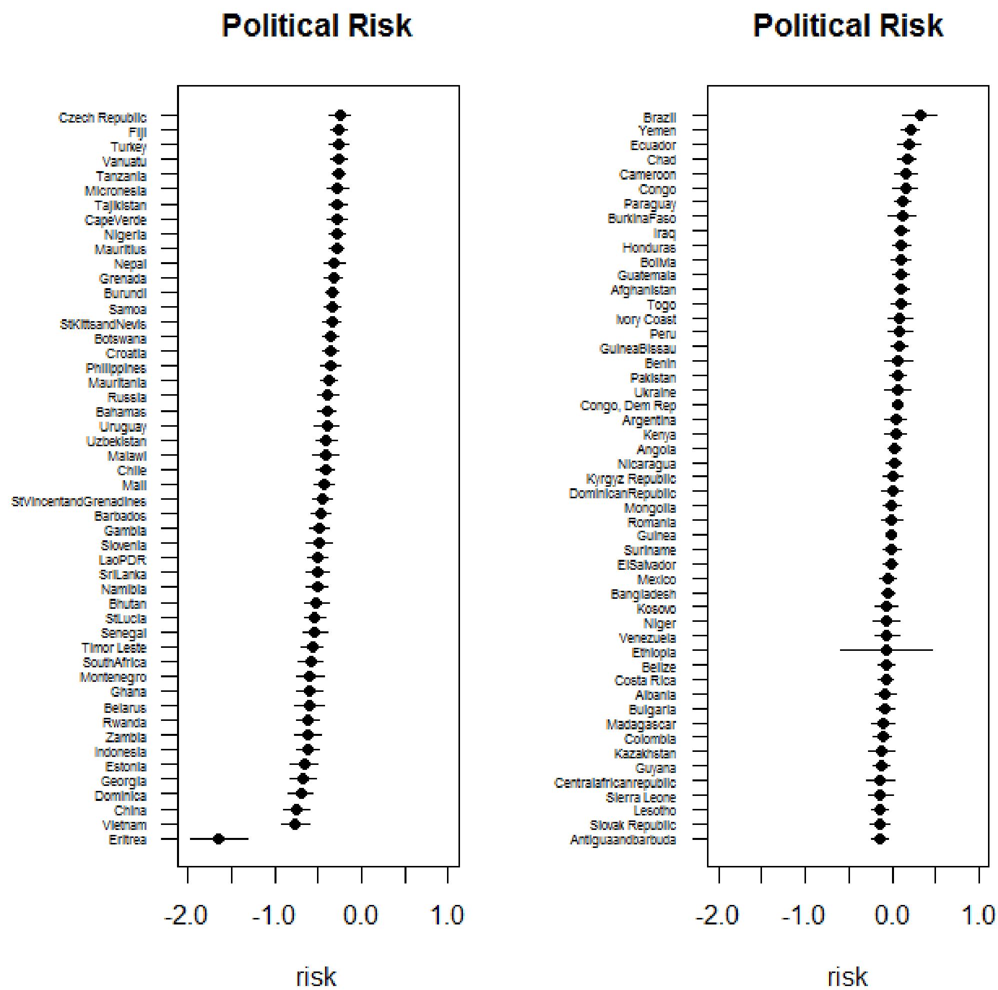

Figure 2: The fifty least (left) and fifty most (right) risky countries from the cross-sectional model.

survey indicators, to properly interpret the subnational estimates the national-level estimates must be added[7]. To some extent, these results reflect what the country-level estimates would suggest: subnational units in Eritrea and China are among some of the least risky, for instance. It also demonstrates that some subnational units are far riskier for business than the country estimates alone would indicate. Mexico, for instance, is not among the riskiest country-level estimates, but two of its regions are in the top ten riskiest subnational units. It also demonstrates the substantial within-country variation that exists but is masked by the country-level estimates.

This, in turn, leads to another useful tool the model produces: the ability to compare subunits

[7]This would not be necessary if there were any indicators that were strictly subnational level, but as written the model estimates subnational risk strictly relative to national level risk, for which there are standalone indicators.

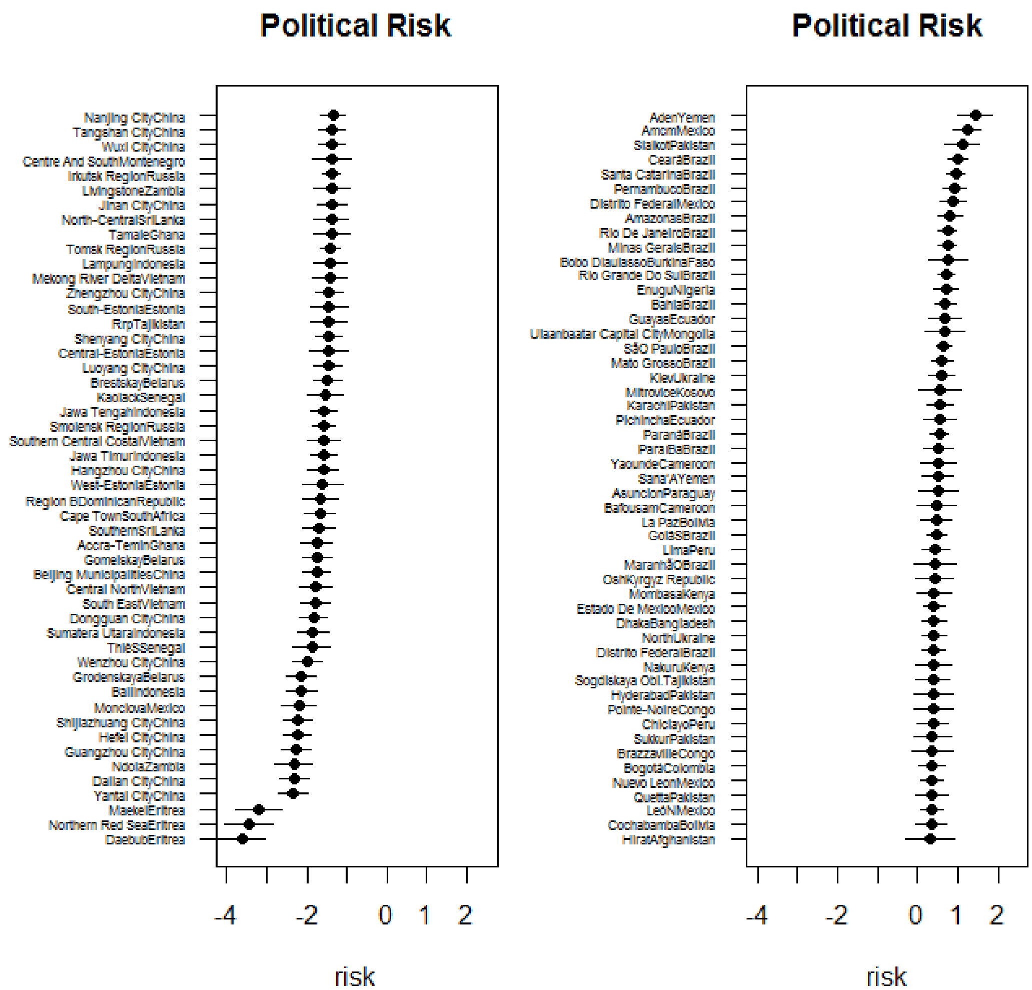

Figure 3: The fifty least (left) and fifty most (right) risky subnational units.

within a country to expose within-country variation in political risk (Figure 4). This is easier to see in a plot where subunits are compared only to one another rather than to other subunits in the world. In Figure 4, the dotted line indicates that country's estimate of political risk, and it is clear to see that some subnational units are riskier and some are less risky than the county-level estimate alone would suggest. Some subnational units exhibit very low levels of political risk, while a few are substantially riskier. For instance, while China is less risky than Turkey as a country, Foshan City poses a greater risk to investors than does any region of Turkey.

Another thing we can learn from these plots is that the source of the greatest risk varies by country. China's country-level risk is higher than that of most of its subnational units. This suggests that the source of the greatest risk in China, according to the model, is the national government rather than any subnational unit, which stands to reason in a country known for the strength of the ruling party's control. In Brazil, on the other hand, the central government appears to be far less risky than any of the country's constituent parts: all but three states within Brazil have a higher political risk score than does the country as a whole. Again, in a country with a strong federal structure, it might make sense that the subnational units may pose a greater threat to investors than would the central government. This also suggests that existing ratings of Brazil that do not take into account the role of subnational governments may significantly underestimate Brazil's political risk. In Turkey, all of the regions are about as risky as the country as a whole, and because the credible intervals for all but Marmara include the country's risk, we cannot say with any certainty that they are not all equivalent. Mexico has regions that are much riskier, and much less risky, than the national goverment, as well as many that are roughly the same.

In addition to allowing us to compare countries, subnational units cross-nationally, and subnational units within countries, this model produces estimates of indicator-specific parameters that allow us to say something about the survey questions and national-level indicators from which the risk scores were estimated (Table 2)[8]. The parameter β indicates how correlated that measure is with the underlying latent trait we are estimating. Because this model uses observable manifestations of the underlying trait as indicators, and the data generating process driving each of these manifestations is noisy and not limited to political risk, we would expect the β estimates to be fairly low. These estimates tell us, for instance, that a firm's perception that corruption is an obstacle and that the courts are unfair are the most strongly correlated with the measure, whereas the expectation of gifts for tax inspectors is very weakly correlated (and, indeed, the estimate is also not statistically significant). Having engaged in expropriation is the single strongest indicator at the national level.

[8]The cutpoint estimates are not discussed here because they are less meaningful when using observable manifestations rather than preexisting ratings. If we think about using rater data, as in Pemstein, Meserve and Melton (2010) and Linzer and Staton (2014), the scale on each indicator is the same— if all indicators are others' estimates of democracy, the scale is democracy— and the cutpoints can be directly compared. This is less true for observale indicators where the scales are all different and the DGP is noisier.

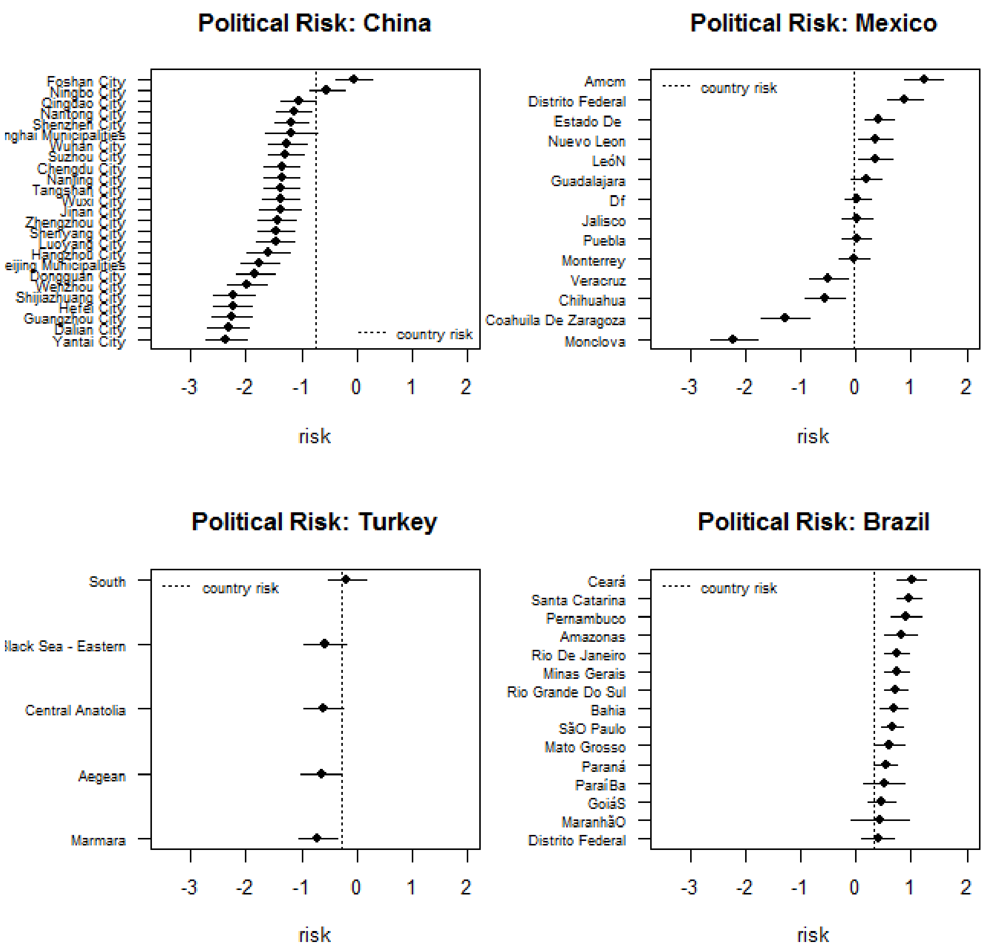

Figure 4: Countries exhibiting substantial within-country variation.

Longitudinal Estimates

Although we obtain the most precise estimates by pooling the data, many applications in which this measure would be useful require time-series data. Further, one might believe that although surveys are not conducted every year, that political risk over any reasonable length of time is probably not static and so a pooled estimate may provide precise but biased estimates. One benefit of a dynamic approach to this hierarchical IRT model is that, although we do not have survey data for each country or subunit in each year, we can obtain estimates of risk for subnational units and countries in years for which we do not have survey data, based on a unit's risk relative to other units and based on its own historical position. The tradeoff here is that we obtain less precise estimates for any given year, in exchange for more and potentially more useful estimates.

indicator	beta	sd
courts	3.02	0.32
govp	1.76	0.26
tax	0.87	0.84
corrupt	4.09	0.44
licperm	2.62	0.30
taxchange	0.64	0.11
bitscase	1.66	0.23
exprop	3.35	1.27

Table 2: Estimates of β for the cross-sectional model. Higher values indicate greater correlation with political risk.

As we would expect, the longitudinal model produces less precise estimates, but exhibits some variation across time (Figures 5, 6, 7, and 8). Both the country-level and subnational risk estimates provide broadly similar results to the pooled model, but they do provide estimates for each year in the sample.

Although the results are similar to the the pooled measure, there are a few interesting differences. While Argentina is one of the riskiest countries in 2008, for instance, it ceases to be in that group by 2011. Notably, in this model Zimbabwe is among the least risky countries in 2008, but jumps to being among the riskiest in 2011. This corresponds roughly with Zimbabwe's treatment of investors. In 2008, the government also introduced an act requiring that all enterprises within the country be at least 51% owned by native Zimbabweans, a move tantamount to expropriation. The regulations to implement the law were put in place in 2010, and the government has defended the act against domestic critics. Notably, the data used in this model do not include the land grabs of 2000. According to a KPMG report, party members have continued to disrupt production agricultural land "including those owned by foreign investors and covered by bilateral investment agreements", and, yet, no investors have brought BIT disputes against them in the time period covered in this analysis[9].

Additional information provided by this model is demonstrated not by looking at a cross-section in any given year, but by looking at how countries and their subunits vary across time. Mexico serves as an illustration in which any cross-sectional rank-ordering would be correct, but would obscure some important information. In the time-series data, we see that while Coahuila, a Mexican state, stays mostly the same over time, Monclova, a city within it, becomes substantially less risky.

[9] KPMG 2012 Zimbabwe Country Profile

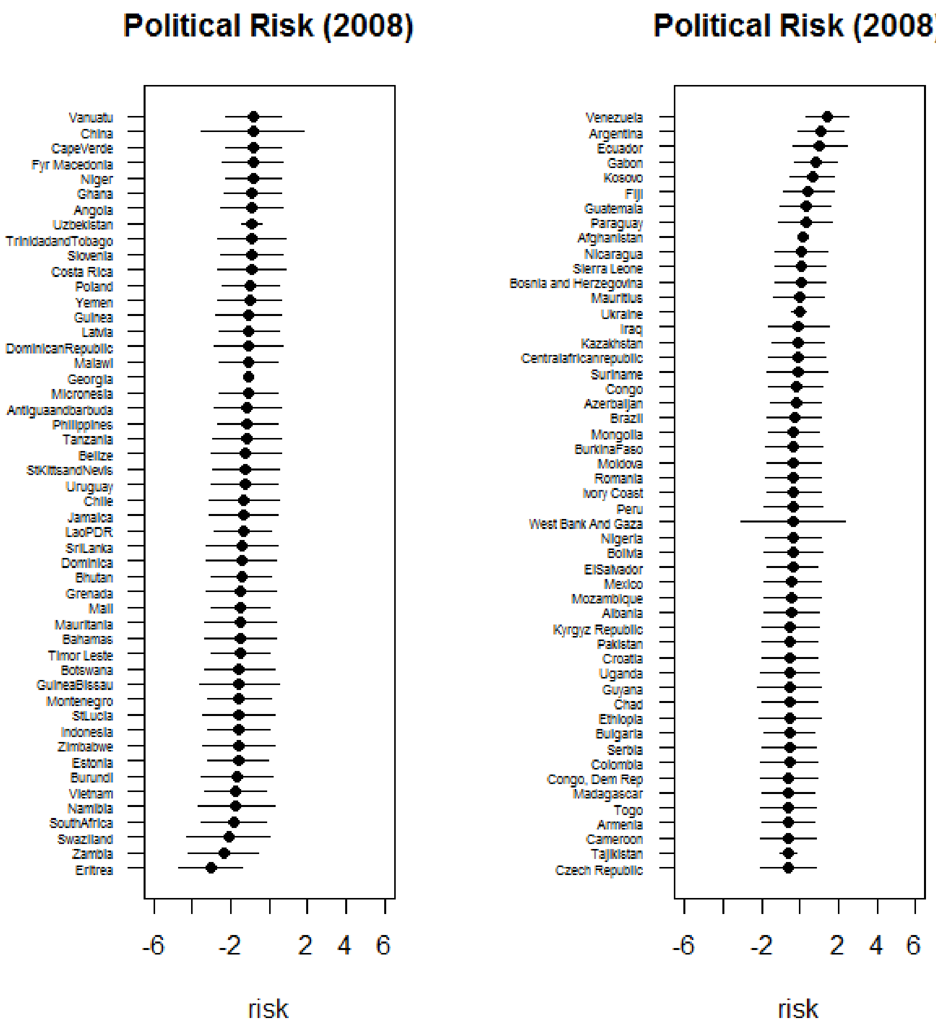

Figure 5: The fifty least (left) and most (right) politially risky countries in 2008.

Veracruz becomes riskier and the others mostly stay the same. Coahuila remains substantially less risky than the other Mexican subdivisions.

The estimates of β for the longitudinal model are substantively similar to those in the cross-sectional model. The indicators most strongly associated with political risk are still expropriation, firms' perception of corruption as an obstacle, having a BIT case filed against a country, and an assessment of how fair the courts are. These indicators provide further evidence that any individual indicator, or an additive index, would not provide a good proxy for political risk, for two reasons. First, it is clear that these elements vary in how strongly they are correlated with political risk, suggesting that an additive index would make very strong and misleading assumptions about any

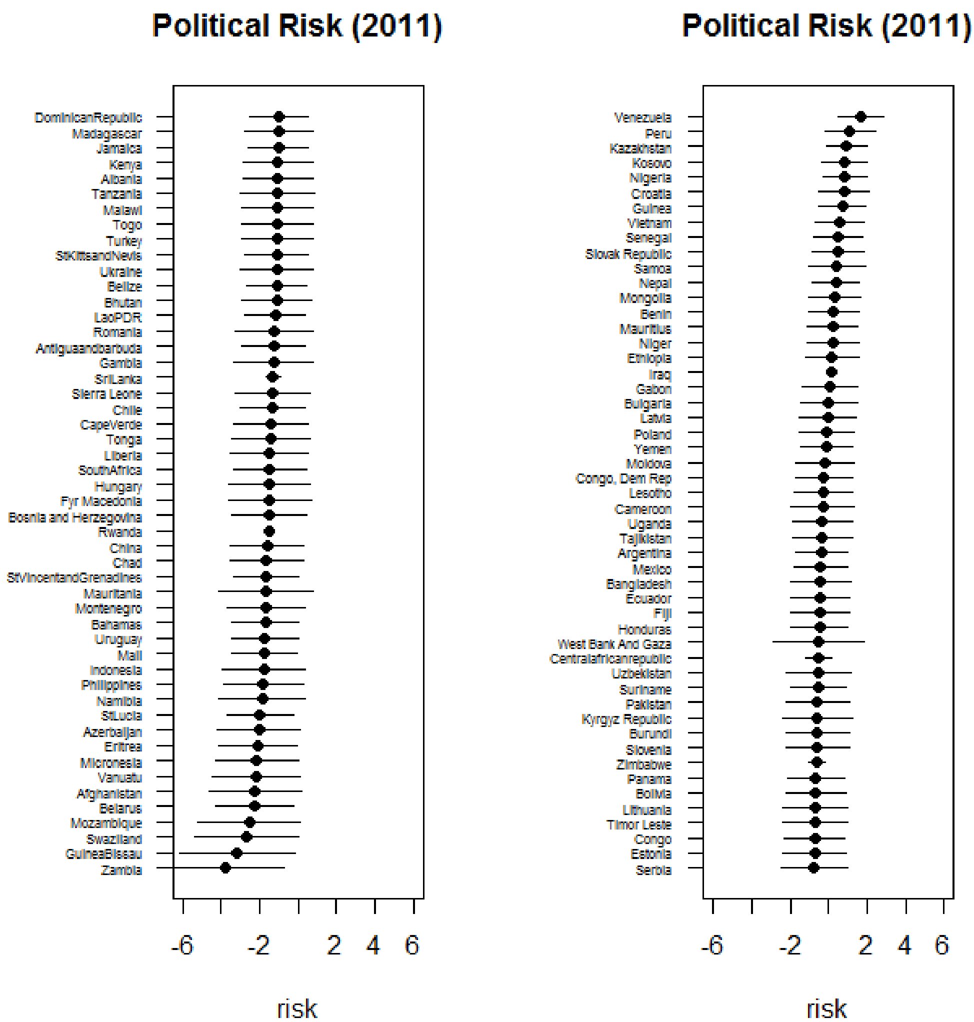

Figure 6: The fifty least (left) and most (right) politially risky countries in 2011.

indicator. Second, the individual indicators that are mostly strongly associated with political risk are either very rare (expropriation) or give no data at the subnational level (bitscase).

Model Fit

Because this model uses observable variables on the left hand side to estimate all the right hand side variables, a model that fits the data well should have right hand side variables that can reproduce the data from which they were estimated. To determine if this is the case, I resampled from the posterior distribution of the estimated parameters, and used these estimates to produce two hundred predicted distributions of each indicator. On average, we should observe that the simulated

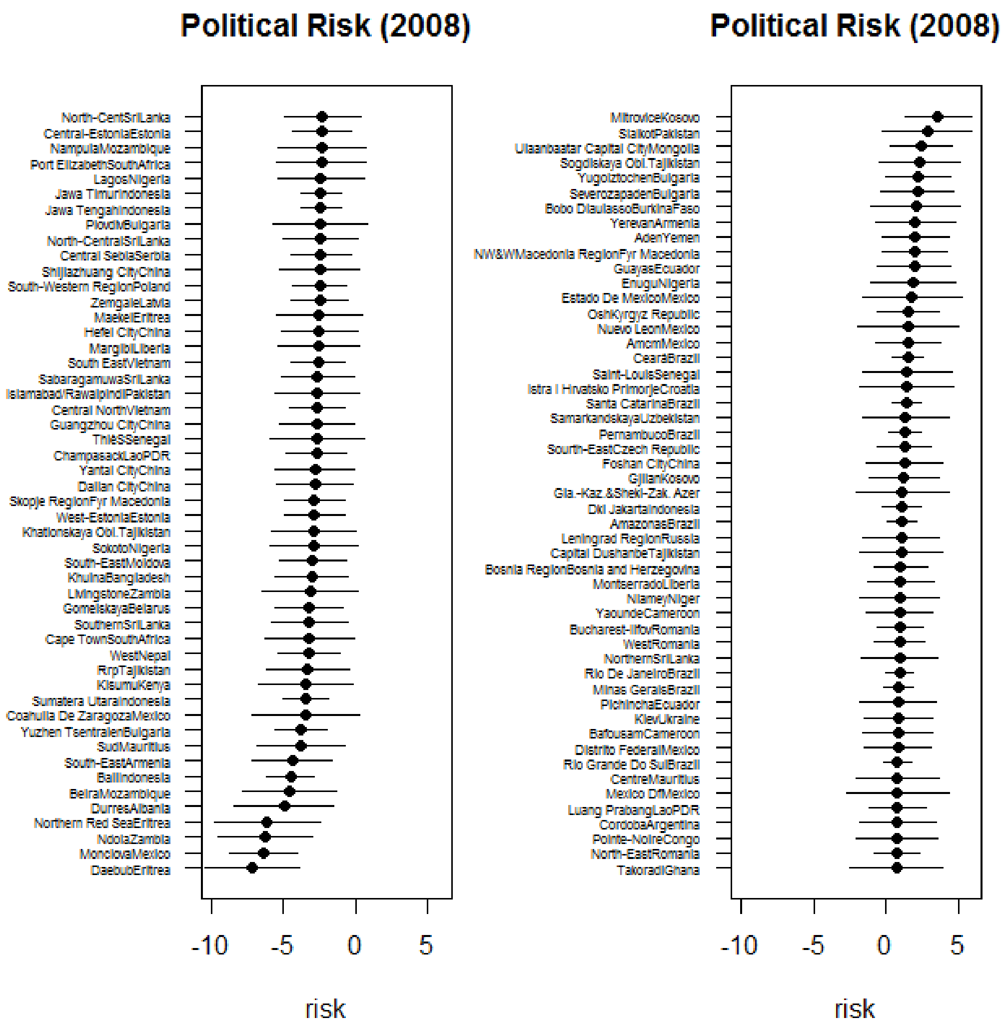

Figure 7: The fifty least (left) and most (right) politically risky subnational regions in 2008.

histograms match the observed distributions of the variables, and for the WES survey indicators, this is indeed what we see (Figure 10). For all of the 20 possible categories (five indicators, each with between 2 and 4 possible categories for answers), the actual observed frequency of the category falls within the bounds of ninety-five percent of the simulated values. The indicator for which the model fit is worst is whether gifts are expected for tax offiials, but even then, the observed value falls within ninety-five percent of the data simulated from the posterior distributon of the parameter estimates.

The same should hold true for the indicators we modeled as a function of only the country-level political risk— the estimates produced by the model should be able to be used to reproduce the

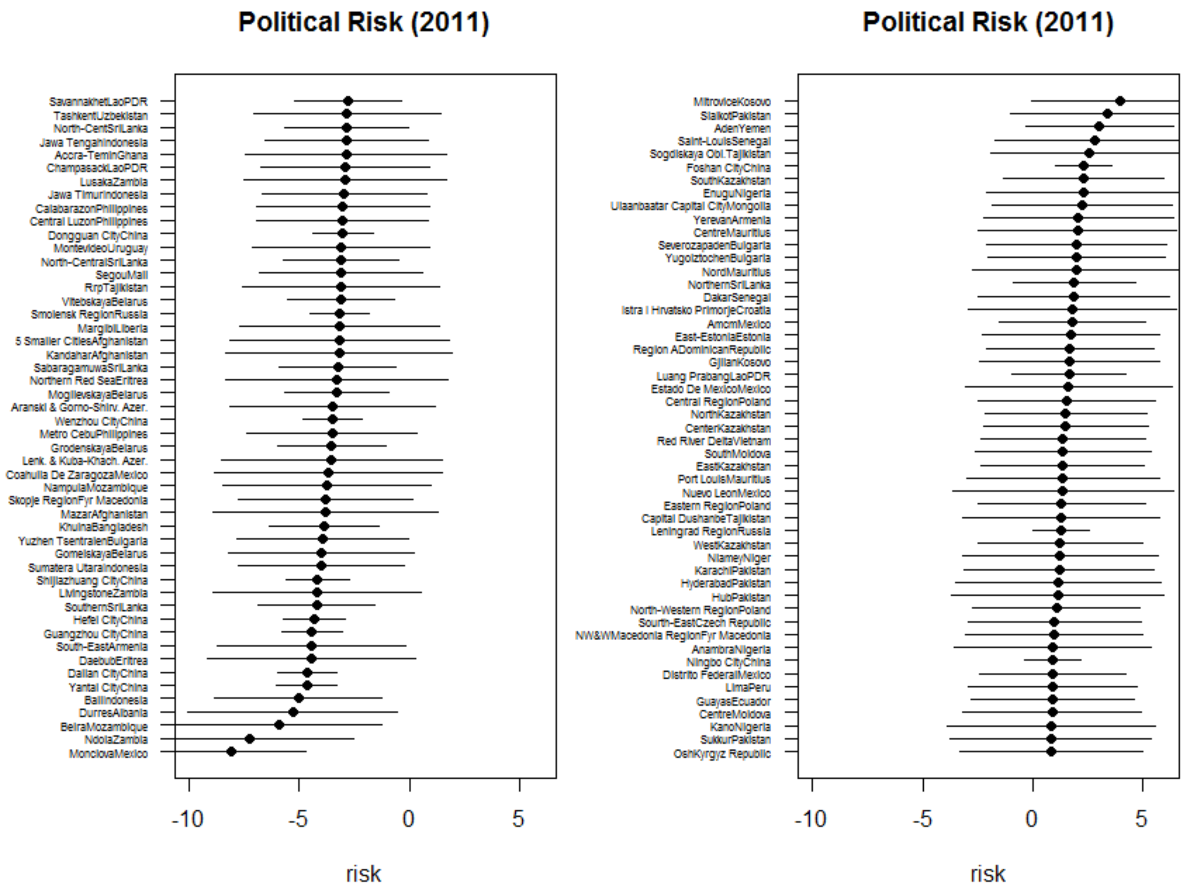

Figure 8: The fifty least (left) and most (right) politically risky subnational regions in 2011.

observable data on average. Again, using the same process as for the survey-based indicators, this is largely what we observe (Figure 11). For the cross-sectional (pooled) model with country-level indicators, the observed frequency falls within a ninety-five percent range of the predicted data 92% of the time, or in all but one indicator-category. The model systematically underpredicts the number of country-years in which no expropriation takes place.

The longitudinal model fits the data somewhat worse than does the cross-sectional model. Although both miss in one category-year, the missed estimate in the longitudinal model misses by a wider margin (Figure 12). It systematically underpredicts the number of country-years in which there was no significant change in the reported corporate tax rate. For every other category-year, the observed frequency falls within a ninety-five percent range of data simulated from parameter estimates from the posterior distribution. In contrast with the cross-sectional model, the longitudinal model seems to fit worst for country-years in which the least risky behavior takes place.

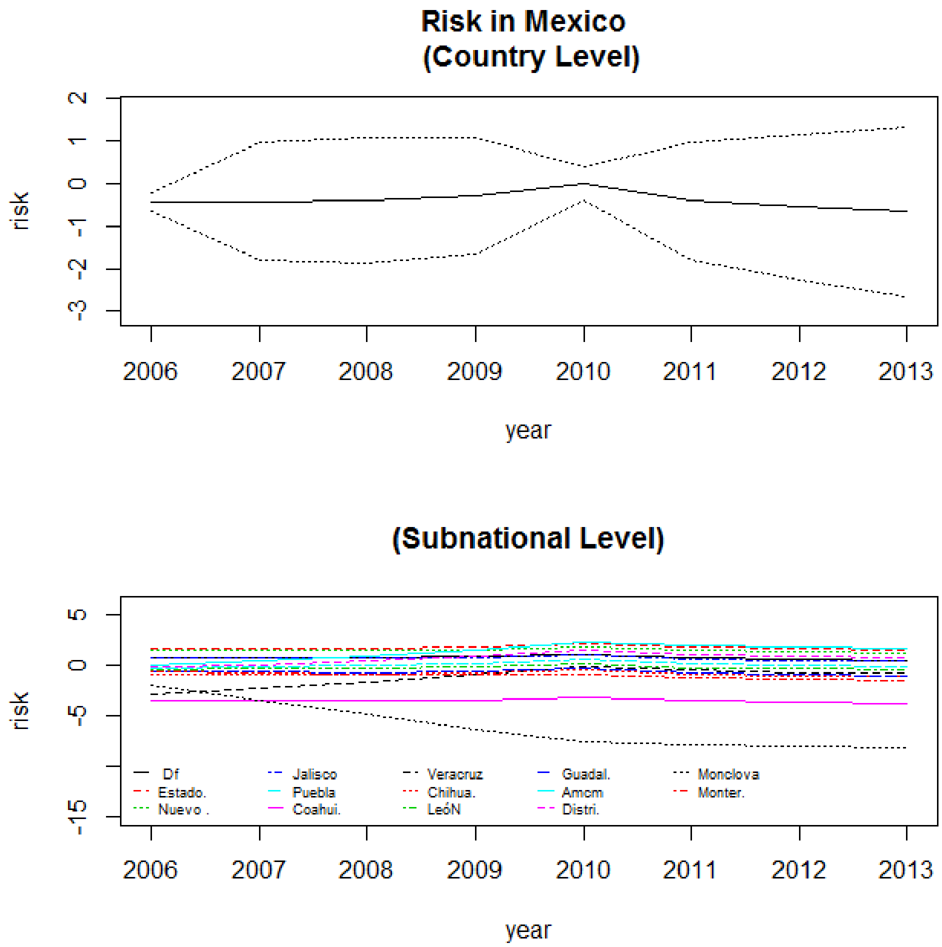

Figure 9: Mexico's within-country variation across time.

Colloquially, the longitudinal model seems to think all country-years are riskier than they really are, and riskier than the cross-sectional model estimates them to be. Like the cross-sectional model, however, the longitudinal model correctly predicts the observed frequencies for the survey data for all indicators (Figure 13).

Conclusion

In this paper, I have presented both a model and a measure. A reasonable criticism of this measure is that the latent variable driving these indicators is not political risk, but corruption. A thorough discussion of to what extent subnational political risk and corruption are theoretically distinct is beyond the scope of this paper, but that criticism of the measure reveals a key asset of the model:

indicator	beta	sd
courts	1.27	0.05
govp	0.78	0.04
tax	0.64	0.37
corrupt	1.78	0.07
licperm	1.17	0.04
taxchange	0.59	0.06
bitscase	1.94	0.25
exprop	2.33	0.36

Table 3: Estimates of β for the longitudinal model.

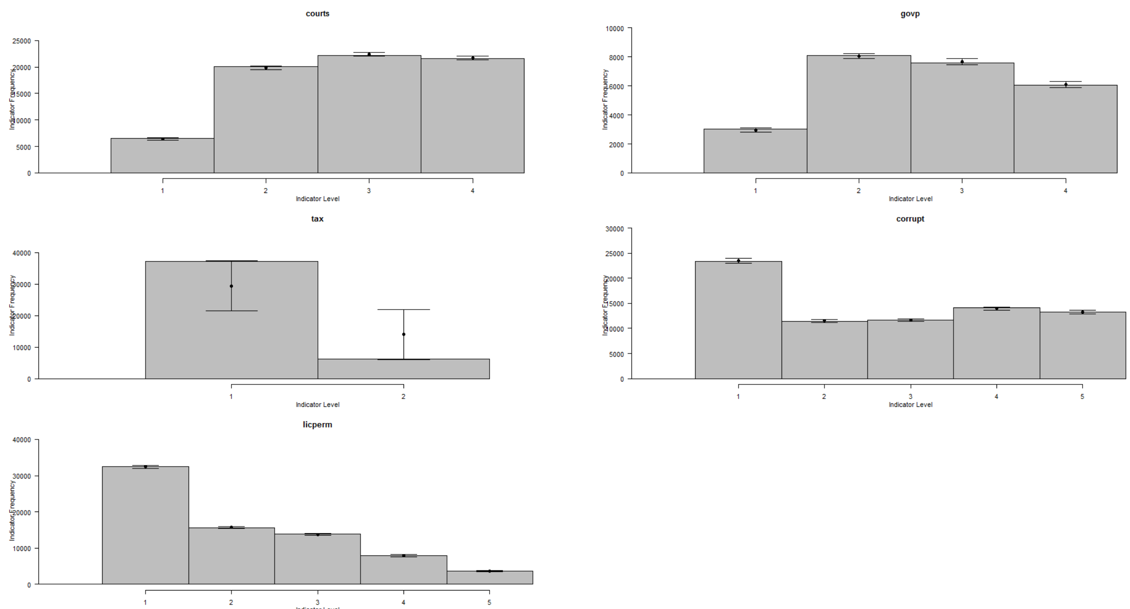

Figure 10: Model fit for survey-based indicators in cross-sectional model.

the model is applicable to any setting in which a latent trait is thought to span levels of a hierarchy with observable indications driven by any or all levels. It is also flexible to the inclusion, exclusion, or substitution of observable manifestations of the latent variable of interest. That is, if an IPE scholar takes exception to the indicators used here, arguing that they are driven by corruption rather than political risk, the model allows him to relatively easily incorporate the manifestations he thinks are appropriate, derive his own measure, and then use it or compare it against the one presented[10]. The model can also be easily updated as more survey data or other indicators become available.

Recently, scholars have become more interested in the role that political risk— the risk that

[10]Replication code for both R and WinBUGS available from author.

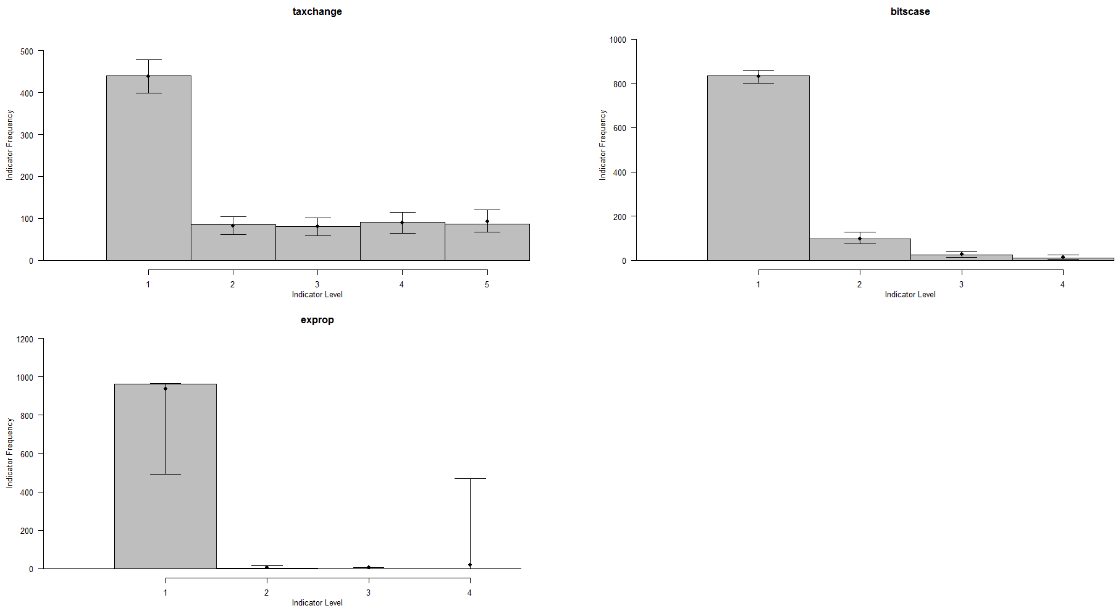

Figure 11: Model fit for country-level indicators in cross-sectional model.

a host country will take actions that threaten the profitability of an investor's operations after the investor has sunk resources into the country and become relatively immobile– plays in the allocation of foreign direct investment (FDI). Although scholars have many theories about how institutions reduce political risk and attract FDI, political risk does not lend itself well to proxies, and the few proxies that do exist tend to be poor conceptual matches, based on proprietary and opaque information, prohibitively expensive, or not widely available. This paper aims to address the problem of measuring political risk by producing both cross-sectional and longitudinal estimates of political risk for both countries and subnational units. This provides a number of benefits: it produces a measure of a latent variable about which theories abound but for which proxies are poor; and it allows researchers to quantify and test theories about subnational variation in political risk, the existence of which is widely known but previously not estimated. It is also flexible, free, and transparent.

In presenting both this model and measure, this paper also accomplishes two other primary goals. First, this paper makes available a model that will allow researchers to estimate latent variables of interest from observable manifestations that occur at and are driven by multiple levels within a hierarchy. This should be valuable to scholars of comparative politics and international relations, as political science is replete with theoretically interesting but unfortunately latent vari-

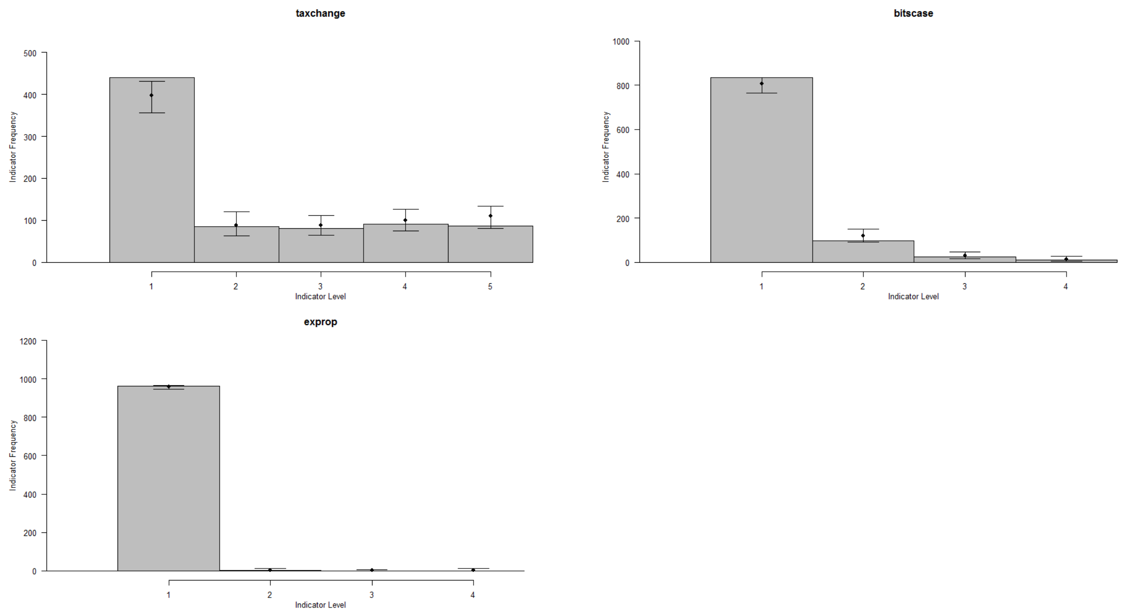

Figure 12: Model fit for country-level indicators in longitudinal model.

ables, and many of these occur in the context of hierarchies. Second, this model uses as indicators firm-level survey responses about government involvement in their operations from the World Enterprise Survey and derives from those responses a single, unified measure, which collapses a valuable but somewhat unwieldy source of information into a more readibly available and useful measure.

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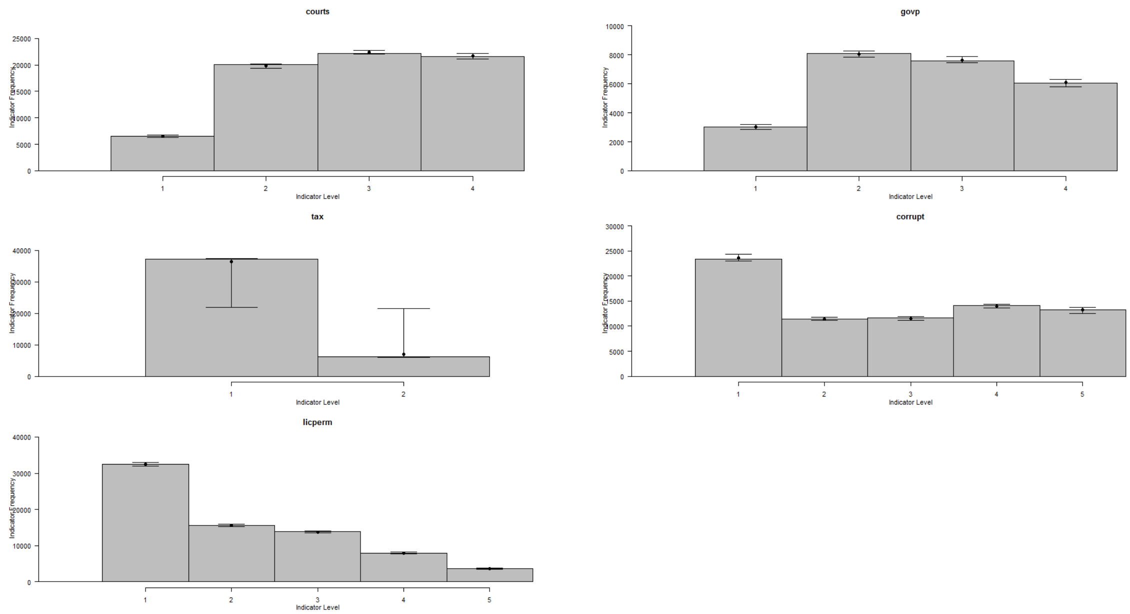

Figure 13: Model fit for survey indicators in longitudinal model.

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A Comparing the Model With Expropriation Indicator and Without

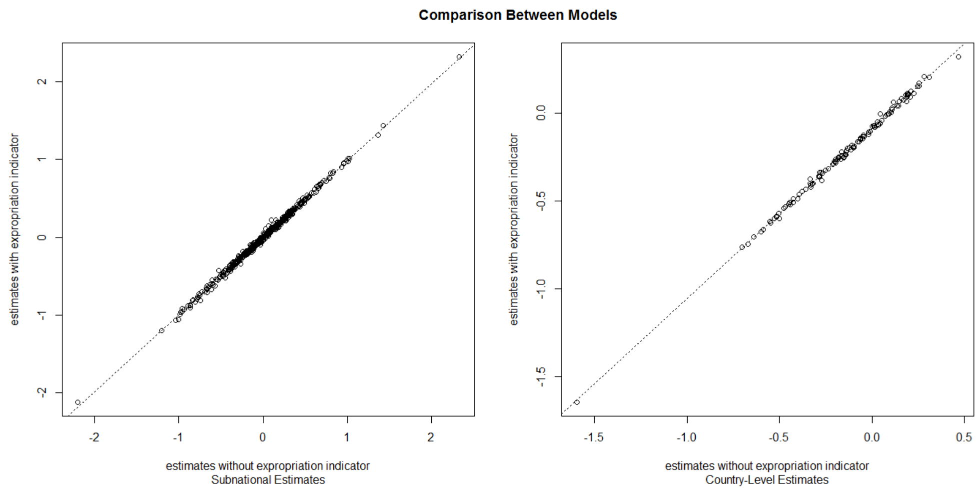

Figure 14: Comparing cross-sectional estimates with and without expropriation. The expropriation indicator, although potentially problematic, is not important to the model.

B Robustness to Uniform Risk Priors

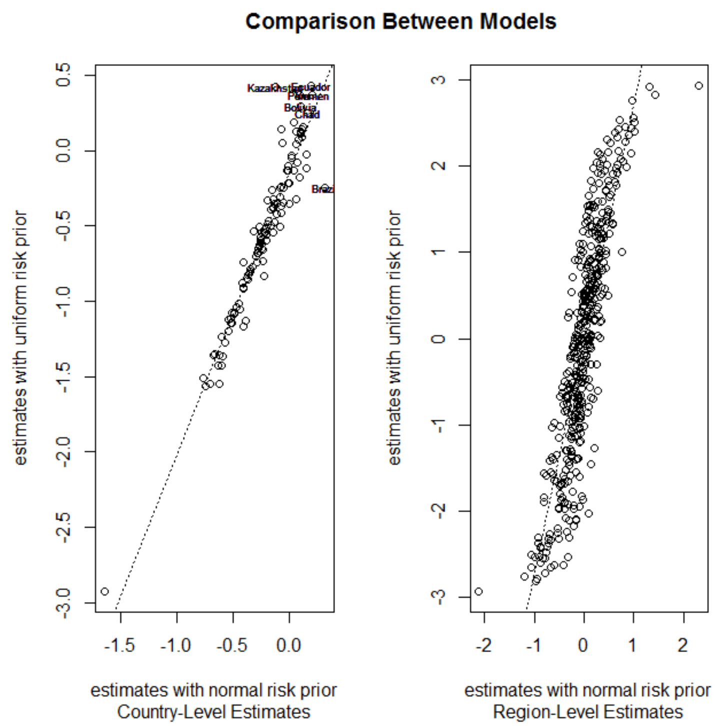

Figure 15: Cross-sectional estimates of national and subnational risk using both normal and uniform priors. At the high end of the scale, the two models diverge slightly in their predictions, but otherwise the models produce qualitatively similar estimates.

C Observations per Country-Year, World Enterprise Survey

	2006	2007	2008	2009	2010	2011	2012	2013
Afghanistan			535					
Albania		304						
Angola	425				360			
Antiguaandbarbuda					151			
Argentina	1063				1054			
Armenia				374				
Azerbaijan				380				
Bahamas					150			
Bangladesh		1504						1442
Barbados					150			
Belarus			273					360
Belize					150			
Benin				150				
Bhutan				250				
Bolivia	613				362			
Bosnia and Herzegovina				361				
Botswana	342				268			
Brazil				1802				
Bulgaria		1015		288				
BurkinaFaso				394				
Burundi	270							
Cameroon				363				
CapeVerde				156				
Centralafricanrepublic						150		
Chad				150				
Chile	1017				1033			
China							2700	
Colombia	1000				942			
Congo				151				
Costa Rica					538			
Croatia		633						
Czech Republic				250				
Dominica					150			
DominicanRepublic					360			
Congo, Dem Rep	340				359			
Ecuador	658				366			
Elsalvador					360			
ElSalvador	693							
Eritrea				179				
Estonia				273				
Ethiopia						644		
Fiji				164				
Fyr Macedonia				366				
Gabon				179				
Gambia	174							
Georgia			373					360
Ghana		494						
Grenada					153			
Guatemala	522				590			
Guinea	223							
GuineaBissau	159							
Guyana					165			

	2006	2007	2008	2009	2010	2011	2012	2013
Honduras	436				360			
Hungary				291				
Indonesia				1444				
Iraq						756		
Ivory Coast				526				
Jamaica					376			
Kazakhstan				544				
Kenya		657						
Kosovo				270				
Kyrgyz Republic				235				
LaoPDR				360			233	
Latvia				271				
Lesotho				151				
Liberia				150				
Lithuania				276				
Madagascar				445				
Malawi				150				
Mali		490			360			
Mauritania	237							
Mauritius				398				
Mexico	1480				1480			
Micronesia				68				
Moldova				363				
Mongolia				362				
Montenegro				116				
Mozambique		479						
Namibia	329							
Nepal				368				482
Nicaragua	478				336			
Niger				150				
Nigeria		1891						
Pakistan		935						
Panama	604				365			
Paraguay	613				361			
Peru	632				1000			
Philippines				1326				
Poland				455				
Romania				541				
Russia				1004			4220	
Rwanda	212					241		
Samoa				109				
Senegal		506						
Serbia				388				
Sierra Leone				150				
Slovak Republic				275				
Slovenia				276				
SouthAfrica		937						
SriLanka						610		
StKittsandNevis					150			
StLucia					150			
StVincentandGrenadines					154			
Suriname					152			
Swaziland	307							
Tajikistan			360					
Tanzania	419							
Timor Leste				150				
Togo				155				
Tonga				150				
TrinidadandTobago					370			
Turkey			1152					
Uganda	563							
Ukraine			851					
Uruguay	621				607			
Uzbekistan			366					
Vanuatu				128				
Venezuela	500				320			
Vietnam				1053				
West Bank And Gaza								434
Yemen					477			
Zambia		484						
Zimbabwe						600		