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Corruption in Space: A closer look at the world's subnations

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Abstract

The level of corruption differs not only between countries, but also between subnations within countries. In this paper we analyze spatial interdependencies in corruption levels for a large sample of 1,232 subnations in 81 countries. Based on a spatial autoregressive model, which additionally corrects for spatial autocorrelation in the error term, we find that a subnation's corruption level is positively affected by neighboring subnations' corruption levels. This suggests that subnational corruption levels are strategic complements. Extending the core model and allowing for heterogeneous spatial interdependencies our results indicate that in particular high income subnations and subnations with a relative low corruption level tend to spill in space. This is due to their high degree of connectivity in terms of economic, sociocultural and political exchange with other subnations. Our findings underline the importance to consider not only a subnation's own characteristics but also their degree of connectivity with other subnations when implementing efficient anti-corruption policies on a local level.

Keywords: subnational corruption; spatial econometrics; heterogeneous spatial impact.

JEL: C21; D02; D73; P48.

1 Introduction

Corruption has a long history of being investigated in economics. Kaufmann (1997) recognises corruption in the public sector as the greatest obstacle to development. Corruption reduces investment and economic growth (Mauro 1995) as well as productivity growth (Del Mar Salinas-Jiménez & Del Mar Salinas-Jiménez 2007). It hampers the effects of industrial policies and fosters the evolution of a private sector that violates tax rules, regulatory rules and environmental rules (Ackermann 1999). According to the Corruption Perceptions Index, which is published by Transparency International, corruption is still a worldwide phenomenon in 2017.[1] The majority of countries in South America, Africa and Asia as well as countries in Southern and Eastern Europe are perceived to have moderate to high corruption levels.

Cross-country differences in corruption levels are explained by a number of factors, including a country's development status, trade openness, religious affiliation, level of education, legal origin, degree and tradition of democracy, size of public sector and wealth in natural resources.[2] However, corruption differs not only between countries but also within countries. In a recent study Mitton (2016) shows that the corruption level can vary significantly within a country. Italy is a prominent example. Northern Italian subnations such as Piedmont, Veneto and Bolzano are significantly below Italy's average corruption level, whereas Southern subnations such as Campania, Calabria and Sicily show a significantly higher degree of corruption than Italy's average corruption level. Factors, which cause the variation in corruption levels within countries are, for example, lower subnational income and larger subnational bureaucracies (Dininio & Orttung 2005, Belousova, Goel & Korhonen 2011) and variations in the levels of inequality, education and wealth of natural resources (Schulze, Sjahrir & Zakharov 2016).

The level of corruption is not only heterogeneous between and within countries, it also tends to cluster in space on a national as well as on a subnational level. Neighboring subnations, alike countries, tend to have similar corruption levels. Becker, Egger & Seidel (2009), Faber & Gerritse (2012) and Jetter & Parmeter (2018) show that countries' corruption levels are characterized by a simultaneous spatial dependence. Recent empirical literature indicates that a similar spatial process works at subnational level. Dong & Torgler (2012), Bologna (2017) and Lopez-Valcarcel, Jiménez & Perdiguero (2017) find spatial interdependencies in the corruption levels of Brazilian municipalities, Spanish municipalities and Chinese provinces, respectively.

In this paper we answer two research questions. Existing literature has either investigated whether corruption spills among countries or among subnations within one country. We ask, whether interdependencies in corruption levels work between neighboring subnations in a broader geographic perspective and irrespective of their national affiliation. The assumption, that the spatial diffusion does not stop at national borders, is plausible and has been inadequately taken in account by the existing literature due to limitations in data availability. We extend the literature by using a novel dataset provided by Mitton (2016), which includes subnational data on institutional quality from a large set of countries. Making use of subnational data, we are able to measure how corruption diffuses within and across national borders, which is especially a merit

[1] https://www.transparency.org/research/cpi

[2] see La Porta, Lopez-de Silanes, Shleifer & Vishny (1999), Paldam (2002), Persson, Tabellini & Trebbi (2003), Serra (2006), Seldadyo & de Haan (2006), Treisman (2007) and Jetter & Parmeter (2018).

when analyzing subnational corruption levels in world regions that are densely nationalized. Europe is such an example where many subnations are located at national borders. Restricting the analysis to within-country information of only a single country would ignore spatial interdependencies working among a large set of subnations that are neighbors but under a different national rule.

The subnations included in our dataset are heterogeneous in their economic, sociocultural, political and geographic characteristics. Recent literature suggests that the strength of the spatial impact is not homogenously distributed between countries, but additional depends on countries' absolute and relative characteristics (Kelejian, Murrell & Shepotylo 2013, Borsky & Raschky 2015). Therefore, in our second research question we ask whether subnations differ in the strength of spatial interdependencies in corruption levels. By answering this research question, we extend the existing literature by determining subnations' characteristics, which drive or hamper their potential to impact the corruption levels of others.

We base our analysis on a sample of 81 countries including 1.232 subnations and a generic spatial model that accounts for the spatial diffusion of corruption on a subnational level. In particular, the model captures two different spatial processes: (i) spatial interdependencies in corruption levels among subnations and (ii) a spatial correlation between idiosyncratic common features of subnations' environments. To account for the simultaneity problem in the spatial process, we use an instrumental variable procedure following Kelejian & Prucha (1998, 1999, 2004) and deploy spatial lags of independent variables as a means of instruments for the subnations' corruption level.

Our results indicate that the degree of exchange between subnations has a significant influence on subnational corruption levels. The corruption levels of subnations act as strategic complements. Their impact decreases with geographic distance. We also find that, among the characteristics of subnations, population size, land area, degree of market integration and resource wealth have a significant effect on the subnations' corruption levels. Further, our results imply that subnations are not homogenous in their degree of interdependencies. We find that in particular rich regions, which generally have a high degree of economic, sociocultural and political exchange, tend to have a stronger impact on the corruption levels of neighboring subnations. Moreover, in line with Kelejian et al. (2013) our results suggest that subnations orientate themselves towards those subnations in the neighborhood that serve as better examples, i.e., which have lower corruption levels.

Our findings have important political implications. First, initiatives to control corruption need to consider subnations' spatial interdependency. Since federal and regional budgets are constraint and widespread institutional policies may be difficult to implement, the design of economic efficient institutional development policies should consider the impact of the spatial interdependencies among subnational corruption levels. Estimates of the impact of anti-corruption initiatives that do not consider spatial interdependencies are downward biased. Second, policies can increase their influence on the level of corruption by considering the heterogeneous structure of the subnations' strength of spatial interdependencies. A tailored policy could make use of this spatial impact to back up anti-corruption policies in subnations, in which the implementation of these policies is difficult, i.e., subnations with a low level of rule of law or regulatory efficiency.

Finally, our findings underscore the relevance of coordinating subnational anti-corruption efforts through regional agreements as proposed in Dong & Torgler (2012).

The paper is structured as follows: section 2 discusses the economic, sociocultural and political channels, which transmit corruption across space and argues why the strength of spatial interdependencies decreases with geographic distance. In section 3 we present our spatial model, address some identification issues and discuss the structure of our spatial weight matrix. Section 4 provides information on the underlying dataset including descriptive statistics and a statistical examination of spatial interdependencies in the level of corruption, our main variable of interest. Section 5 presents the results for our main model and for the extended models allowing for heterogeneous spatial interdependencies. Further, a set of robustness exercises are presented. Section 6 concludes.

2 Spatial process of corruption

A variety of mechanisms work in diffusing corruption across space (i.a., Kelejian et al. 2013). All of them are grounded in some type of economic, political and sociocultural exchange that jointly contribute to subnations' connectivity. The strength of the diffusion depends on proximity, i.e., the closer two subnations are, the stronger is their degree of connectivity.

2.1 Channels of diffusion

Economic exchange happens mainly over trade in goods, services and capital. Levchenko (2016) argues, when viewing institutions as equilibrium outcomes, there are broadly two reasons, why trade leads to a change in institutions: First, trade may change the balance of political power, which induces a change in the quality of institutions. This change does not necessarily bring an improvement, but can also be a deterioration as modelled in Do, Levchenko et al. (2009) and empirically shown by Stinchcombe (1995) on the example of Caribbean sugar economies. Second, trade may alter agents' preferences for the quality of institutions. The economic exchange entails an exchange of knowledge and ideas, which change beliefs, preferences and expectations of domestic agents, including common understandings of a socially acceptable business behaviour. Usually, the behaviour of others is important for ones own understanding of compliance with prevalent rules (Dong & Torgler 2012). This notion is reflected in Aoki (2001)'s definition of institutions as common beliefs that are sustained and changed in the strategic interactions of agents. Following Aoki (2001), economic exchange with non-domestic business partners may affect domestic agents' preferences, expectations and beliefs on a socially acceptable behaviour and alter their action choices. Firms operating in a subnation with a low corruption level may demand and push for a less corruptive environment as a prerequisite to economic exchange with other subnations. Ongoing economic exchange with business partners from a less corrupt neighboring subnation may change beliefs and expectations of own economic agents, which adopt by gradually reducing own action choices involving corruptive activities. However, the strategic interaction mechanism may also work the other direction. Starting or intensifying economic exchange with business partners used to operate in a more corrupt environment may increase the domestic corruption level, if adopting a more corruptive business behaviour becomes the best response of domestic economic agents in strategic interactions. At the end, which direction in the diffusion of corruption is stronger remains an empirical question.

The sociocultural exchange channel mainly works over migration. The mechanism on how migration contributes to the diffusion of corruption across space is similar to the one of the economic exchange described above. People diffuse their ideas, knowledge as well as preferences, expectations and beliefs on socially acceptable behaviour in all kind of social interactions. Dong & Torgler (2012) present an interaction-based model, which predicts that the level of corruption is positively associated with social interaction. In their model, the corrupt decision of a bureaucrat depends on his expectation of others' decisions. Migration can deliver an impetus for a change in common beliefs and actions towards more or less corruptive activities. Migrants become domestic agents and domestic agents have a variety of roles, in which they contribute to upholding and changing expectations and beliefs on socially acceptable behaviour. They, not only, hold their economic role of entrepreneurs, workers or consumers, but also their social role as neighbors or parents and their political role as council members and other political functions.

Lastly, we consider the channel of political exchange. Institutions may be harmonized through the national political authority as well as supranational or foreign authorities enforcing common rules. Accession to the European Union, for instance, requires acceptance of laws and a quality of institutions similar to those in existing member countries. Even before accession, institutional change is, for example, a prerequisite for participation in preferential trade agreements. Grilli (1997) and Winters (1993) argue that this was particularly important for the neighbors of the European Union in the 1990s. Today, countries are members of numerous international agreements, like agreements on specific environmental or labor standards, which require the uptake of a specific common level of institutional quality and regulation. Also, governments may decide on their own to adopt institutions from other governments. They may want to seek harmonization of economic rules in order to attract non-domestic business partners and investors. Likewise, in pursuit of market enlargement, non-domestic business partners and investors may demand from governments to change an institutional environment to conform to common principles (David 1996). When governments are in competition, they may want to adapt their institutional quality in order to provide a trade and investment friendly institutional environment (Qian & Roland 1998). In line with that, Ward & Dorussen (2015) argue African governments improve their quality of institutions in strategic interaction competing for aid donation and foreign direct investments.

Some of the economic, sociocultural and political channels of exchange that affect today's corruption levels are working at the present time. A good example are the ongoing negotiations between the European Commissions and the heads of the Western Balkans on institutional prerequisites for an EU membership, which includes a reduction of corruption levels (European Commission 2018). Other channels have worked a long time ago, but their impacts are still reflected in today's corruption levels. Prominent examples for a historical political exchange with current institutional consequences are political annexations in the era of imperialism in the late 19th century. There is a vast number of literature on the colonial legacy of good and bad institutions (Acemoglu, Johnson & Robinson 2001, Djankov, La Porta, Lopez-de Silanes

& Shleifer 2002, Djankov, La Porta, Lopez-de Silanes & Shleifer 2003). Institutional legacies of imperialism are not only found at the national level. Because of historical displacements of national borders there is also subnational variation in the quality of institutions, which can be traced back to historical imperialism (Becker, Boeckh, Hainz & Woessmann 2016). Alike historical political events also historical trade centers and historical migration flows may have their legacy reflected in present day's corruption levels.

2.2 Diffusion at a cost of distance

Kelejian et al. (2013) argue that institutional diffusion is likely to occur more often and stronger between neighbors. Neighboring subnations are more connected, because they have a higher degree of economic, sociocultural and political exchange. In trade literature geographic distance is the most robust proxy for trade costs. Trade partners, which are closer to each other, are in a more intense exchange of goods and services (see Limao & Venables 2001, Anderson & Van Wincoop 2004, Disdier & Head 2008). This holds for trade at the national and at the subnational level, likewise. Hillberry & Hummels (2008) find that trade within the US is heavily concentrated at the local level. They argue that producers co-located in supply chains to minimize transportation costs, to facilitate just-in-time production, to benefit from informational spillovers and exploit other associated agglomeration effects.

Sociocultural exchange increases with similarity. Since residents of closer subnations are more likely to have a common history, culture, language and ethnical background (Goldscheider 1973), the intensity of sociocultural exchange is determined by geographic distance. As stated as the first of Ravenstein's laws of migration: most migrants move over relatively short distances (Ravenstein 1885). Migration flows at subnational level are significantly larger than that between countries. According to the International Organization for Migration and The World Bank, and without accounting for seasonal and temporary migrants, in 2016 more than 1 billion people lived outside their places of origin, with about 740 million of them classified as internal migrants (Sorichetta, Bird, Ruktanonchai, zu Erbach-Schoenberg et al. 2016). The distribution of migrants within a country seems to be rather uneven and different migrant groups usually exhibit different migration patterns (Van Der Gaag & Van Wissen 2001). Economic migrants seek employment and social migrants seek family reunification. Nevertheless, literature shows that there is an overall trend of a redistribution of population from rural to urban areas or from urban to even more urban areas within countries (Champion 2001).

Geographic distance also matters for political exchange. Adapting institutions as well as governments learning from each other happens more often between neighbors (Bikhchandani, Hirshleifer & Welch 1992). As geographically close units face similar challenges and share a greater deal of environmental factors, neighbors' institutions are more likely to meet domestic requirements (Murrell, Dunn & Korsun 1996). Berkowitz, Pistor & Richard (2003) show that institutional transplants between geographically close countries are more likely to be receptive than transplants between distant lands. Mukand & Rodrik (2005) model the institutional learning decision with countries choosing between experimentation and imitation. Countries closer to a successful one choose imitation. Again, more political exchange between neighbors is not only valid for national governments, but also for subnational ones. Subnations are even more similar in their challenges and environmental factors, which is also due to their vertical integration under the same national rule.

All of the arguments presented in this section suggest that the level of economic, political and sociocultural exchange is highest between immediate neighbors and decreases with geographic distance. Subnations, which are closer to each other, are more likely to share similar market structures, governmental structures and sociocultural backgrounds and are, therefore, more connected.

3 Empirical implementation

We specify a generic spatial model that accounts for the spatial diffusion of corruption on a subnational level. In particular, the model captures two different spatial processes: (i) a spatial correlation between corruption levels among subnations and (ii) a spatial correlation between idiosyncratic common features of subnations' environments. Our model is given by following specification 1,

$$\begin{aligned} y_{ic} &= \rho \sum_{j=1}^{J} \omega_{ij} y_j + X_i \beta + \theta_c + \mu_{ic} \\ \mu_{ic} &= \lambda \sum_{j=1}^{J} \omega_{ij} \mu_j + \varepsilon_{ic}, \end{aligned} \tag{1}$$

where y_{ic} is the corruption level of subnation i in country c, ω_{ij} is a spatial weight assigned to subnation j by subnation i. y_j is the level of corruption in subnation j, and ρ is the corresponding parameter of interest. Interdependencies in corruption levels due to economic, political and sociocultural exchange between subnations manifest in a statistically significant estimate of ρ. A nonzero coefficient estimate implies that a subnation's corruption level is determined by the corruption levels of other subnations. In line with our discussion in section 2 we expect ρ to be positive, meaning that the corruption levels of subnations in a geographically close neighborhood are strategic complements. The null hypothesis is that there are no spatial interdependencies in the corruption levels of subnations, which denotes that they are determined independently from each other. Additionally, a subnation's level of corruption is defined by a set of own subnational factors, X_i, which vary within countries. θ_c are country dummies, which capture all country-specific influences, which do not vary over a country's subnations, for example, a country's legal origin, degree and history of democracy, political stability, membership in the European Union or other multilateral agreements that hold for all administrative units of a member country. Finally, μ_{ic} is the error term, which is allowed to be spatially correlated, where λ is a parameter that reflects the strength of spatial correlation between subnation i and subnation j and ε_{ic} is a well-behaved error term.

To account for the simultaneity problem in the spatial process as defined in equation 1, we use an instrumental variable procedure following Kelejian & Prucha (1998, 1999, 2004) and deploy spatial lags of the independent variables as a means of instruments for the corruption level of subnations$_{-i}$. In particular, the procedure consists of three steps. First, the regression parameters in equation 1 are estimated by a two stage least squares estimator using the subnation specific independent variables, X_i, and the spatial lags thereof, WX_i, as instruments for y_j. In this step, the spatial correlation in the errors is ignored as only a consistent and not an efficient estimation of the coefficients is necessary. In the second step, the residuals from the first step are used to estimate the autoregressive parameter λ in the disturbance process. For this a generalized method of moments procedure as developed in Kelejian & Prucha (1999) is employed. In a third and final step, the estimate of λ is used to transform the model into a spatial version of a Cochrane-Orcutt procedure. This transformed model is then estimated again by a two stage least squares procedure using the same instruments.

An alternative approach to address the inherent endogeneity in spatial models is a maximum likelihood approach as proposed by Anselin (1988). Our decision to use the instrumental variable approach was based on three reasons. First, based on the instruments choice as described above, Das, Kelejian & Prucha (2003) show that the instrumental variable estimator is almost as efficient as the maximum likelihood approach. Second, in contrast to the maximum likelihood approach the instrumental variable estimator does not rely on the normality assumption. And finally, as criticized by Gibbons & Overman (2012), the maximum likelihood approach requires prior knowledge of the data-generating process, whereas the instrumental variable estimator allows to estimate equation 1 structurally.

3.1 Identification issues

Recent literature points at two ways how the identification of spatial interdependencies could be impeded. First, data on corruption levels and/or independent variables is missing for some subnations. Missing data problems in spatial models are particularly problematic, because parts of observations relating to one unit are simultaneously used as explanatory variable for other units. We deal with this problem in the following way. In our baseline model we ignore subnations, for which we do not have information on corruption levels. In the literature this procedure is also known as listwise deletion. Kelejian & Prucha (2010*a*) show that, as long as the number of missing endogenous variables is small relative to the fully observed sample, the two stage least squares instrumental variable estimator stays asymptotically consistent. As in our sample the number of observations with missing data is relative small compared to subnations, which are fully observed, we are confident that the potential bias of ignoring these observations is negligibly small.[3] However, in a robustness exercise in section 5.2 we apply an estimation procedure, as laid out in Kelejian & Prucha (2010*a*) and Kelejian et al. (2013), which explicitly takes the structure of the missing data into account.

A second identification issue is, that spatially correlated, i.e., common to a group of geographically close subnations, unobservable determinants of corruption levels might affect the estimate of spatial interdependencies in corruption. It is likely that subnations in the neighborhood share common environmental conditions or shocks that influence their corruption levels.

[3] In our sample 838 subnations are fully observed, whereas for 394 subnations data on the corruption level of some directly neighboring subnations is missing.

We address this issue, which might violate the assumption of an i.i.d. error term, by allowing for a spatially correlated error term. This enables us to differentiate the causal effect of one subnation's corruption level on the other subnations' corruption levels working via economic, political and sociocultural exchange from the potential impact of unobserved common subnation-specific factors, given the spatial model is correctly specified . Finally, concerning the bias stemming from omitted common factors, Kelejian et al. (2013) show that the two stage least squares instrumental variables estimator is in particular suited to deal with this issue.

3.2 Spatial weight matrix

Following the discussion in section 2, we base our spatial weight matrix on geographic distance. Spatial interdependencies in subnational corruption levels are affected through various channels. Economic exchange is stronger for subnations, which are closer to each other. The harmonization of institutions through political exchange happens more often between geographically close subnations. Neighboring subnations are more likely to have a common history, culture, language and ethnical background, which will lead to a more intense exchange. We are confident that geographic distance is highly correlated with true interaction and, thereby, it is well fitted to capture the strength of spatial interdependencies stemming from these channels.[4]

In our core spatial weight matrix we use the inverse distance between the center of two subnations to define each off-diagonal element of the spatial weight matrix ω_{ij}. Since no subnation is considered as its own neighbor, $w_{ii} = 0$. This weighting scheme assigns closer subnations a stronger degree of spatial interdependencies, which linearly decreases in distance. Further, we assume that the influence on a subnation's corruption level by others is limited to subnations within 500 kilometer distance. Every subnation outside this distance range does not exert influence and enters the weight matrix with zero. Thereby, we emphasize the local confined spatial exchange at the subnational level as shown, for example, by Hillberry & Hummels (2008). This procedure of limiting the spatial influence is also known as distance band. To sum up, the strength of spatial interdependencies between two subnations is defined as

$$\omega_{ij} = \frac{1}{d_{ij}} \quad if\ d_{ij} \leq 500\,km$$
$$\omega_{ij} = 0 \quad otherwise.$$

We make two assumptions on the spatial weight matrix. First, we assume that subnations are only affected by subnations within a 500 kilometer distance band and that the spatial impact decreases linearly in space. Second, we assume that the total spatial dependence is homogeneous for subnations. This means that the degree of spatial interaction cannot be larger than one independently from the number of subnations in the neighborhood. Therefore, we row normalize the spatial weight matrix by dividing each weight by its row sum. The element ω_{ij} can then be

[4] Another advantage of geographical distance is, that it can be considered exogenous. Weight matrices based on socioeconomic measures tend to be endogenous, which leads to bias and inconsistent estimates (Kelejian & Piras 2014). Qu & Lee (2015) discuss estimation methods to estimate spatial autoregressive models with an endogenous spatial weighting matrix with regard to consistency, asymptotic normality and finite sample properties.

interpreted as the share of the overall spatial influence on subnation i from subnation j. This type of normalization has recently been criticized in the literature (see Neumayer & Plümper 2016) as it is inferential not neutral and, therefore, needs to be theoretically motivated. In our case, we are analyzing subnations in very heterogeneous geographical settings, for example, densely clustered regions in central and southern Europe as in comparison with sparse subnational regions in Russia or Kazakhstan. Row-normalization allows us to account for this setting so that the average influence of an individual subnation in a densely clustered region is lower than for an individual subnation in a sparse region. In section 5.2, we will relax both of these assumptions.

Finally, it has to be noted that there is no theoretical guidance on the functional form of the weight matrix that captures the true spatial process of corruption. Many different spatial weight matrices are plausible. To account for this, we apply alternative definitions of the weight matrix in the robustness section 5.2.2 to get a better understanding about the spatial process and to see how sensitive our results are with regard to the choice of the spatial weight matrix.

4 Data and summary statistics

We utilize cross-sectional data of 1,232 subnations from 81 countries around the world for the year 2005.[5] The majority of subnational data is at the first level of administrative divisions (ADM1) of the respective countries, for example, states in the U.S., provinces in Panama, regions in Tanzania. For the European Union, subnational data is available for NUTS 2 or NUTS 3 regions, for example, states in Austria and Germany, regions in the Slovak Republic, autonomous communities in Spain. Table B1 in the appendix reports the decomposition of subnational data by country. In general, our sample provides quite an even split of data on more and less wealthy economies. Categorizing according to the World Bank Analytical Country Classification[6] in 2005, our sample includes 554 subnations from upper middle to high income countries and 678 subnations from low to lower middle income countries. The threshold lies at a gross national income per capita of 3,466 USD in the year 2005.

4.1 Corruption data

Our measure for subnational corruption levels is an index constructed from survey questions, that fall within the category of local corruption from six different sources, and which were collected and merged into one dataset by Mitton (2016). Each of these sources provide separate corruption measurements for different subnations within each country on either respondent-level or subnational level. Five sources are surveys collecting data on corruption from civil societies and covering different world regions: Afrobarometer survey, Latin American Public Opinion

[5] We base our analysis on the year 2005 as this is the year on which our main variable of interest, the level of corruption, is based on. We are confident, that the main causal mechanisms, which determine the spatial interdependencies in the corruption levels, have not changed significantly over time. Subnational GDP, which is not available for 2005, is adjusted with GDP deflators to be comparable to 2005 data. For some subnations and survey questions information on the corruption level stems from the years 2006-2011. See Tables B2 - B7 in the appendix for more information on the data.

[6] http://databank.worldbank.org/data/download/site-content/OGHIST.xls

Project, Asia Foundation survey, Quality of Government Institute survey and Latinobarómetro survey. Data from the World Bank Enterprise survey adds additional information from enterprises and experts on the prevalence of corruption in subnations of countries around the world. Survey questions that relate specifically to country-level institutions are excluded to ensure that the responses reflect the local situation in the subnational region as much as possible.[7]

We apply the same method of aggregation as Mitton (2016) to construct our index on subnational corruption levels, however, we choose the opposite direction of coding. First, we aggregate the data to the subnational level, clean it, put it into the same direction of measurement and standardize it to a mean of zero and a standard deviation of one so that all questions are weighted equally when aggregated. Then, we construct our index on the level of corruption by first averaging the standardized data for all questions within each survey and then aggregating the data between the different surveys. We thereby obtain one measure for each of the 1,232 subnations, which lies between the range of -5.661 and $+2.990$. The sample mean is at -0.055. A higher value indicates a higher corruption level in the subnation. The measure on the level of corruption is based on perceptions of respondents on broadly three dimensions: (i) their assessment to what extend local government councillors, officials, police officers, judges and magistrates are involved in corruption, (ii) to what extent they believe that the local government combats corruption and (iii) their personal experience on how often they had to make informal payments or gifts to get a document or permit in a public office, a child into school, a household service, medical attention, to avoid problems with the police or to get help from the police.

Our index on the level of corruption is primarily a de facto measure of subnational corruption levels, since it is based on perceptions of survey respondents. Despite the potential problems of subjectivity, the perception-based indicator is a valuable carrier of information on actual corruption and seems to capture very closely the real phenomena. Another important issue to consider is a potential bias due to measurement error. The data on corruption is collected from experienced organizations and based on information taken from 172,057 respondents around the world. This ensures that the compiled statistics are not unduly influenced by a small number of uninformative responses. Cultural bias is a common concern in cross-sectional survey data as respondents of different societies may respond differently to questions based on societal norms. We account for this issue by using country dummies in our regressions, which capture any cross-country cultural differences. We expect this mitigates the issue of cultural bias and leaves only bias stemming from within country variation in societal norms, which we believe to be relatively small.

4.2 Independent variables

Literature on the determinants of corruption predominately stresses the role of national factors. Empirical studies find significant and robust results that a country's economic development status, level of international integration, political stability and democratic tradition, legal origin,

[7] Tables B2 - B7 in the appendix list the questions from which data is taken, provide information on the data sources and the direction of coding.

size and structure of the government, religious affiliation, ethno-linguistic fragmentation, latitude and fuel exports influence corruption levels.[8]

National factors, however, cannot explain the observed within-country variations in corruption levels. Besides controlling for country characteristics, which are invariant over subnations, we, therefore, control for a set of independent variables on subnational level. Our choice of independent variables includes socioeconomic, cultural, political, geographic and resource endowment factors that are commonly used in existing literature and show a certain degree of within-country variation.

As socioeconomic factors we consider GDP per capita, the size of population and average years of schooling at the subnational level. We further control for the number of seaports, number of airports and a dummy for the capital city as proxies, which capture the effects of market integration and urbanization. As a cultural factor with subnational variation we use ethnic fractionalization. As a political factor we control for the effect of having subnational political and administrative autonomy. We use a set of variables on subnations' geography and natural resource endowment, which includes a subnation's geopolitical position, its size of land area, accessability, risk of experiencing natural disasters and endowments in precious metals, diamonds, oil and gas. Table B9 in the appendix reports details on definitions and data sources on the independent variables. For many of these variables we draw back on Mitton (2016), who set up a comprehensive dataset including economic, institutions, geographic, climate and natural resource variables at the subnational level.

4.3 Descriptive statistics

Table 1 reports the summary statistics of the 1,232 subnations from 81 countries around the world, for which we have information on their corruption levels. The dependent as well as the independent variables show a substantial degree of subnational variation also within countries. To give an example, the Aosta valley in Northern Italy scores -1.029 in the corruption index, which ranks it 73 in our sample. Calabria in Southern Italy scores +1.105 in the corruption index, which ranks it 1.164 in our sample. Italy's Northern subnation Aosta valley has a corruption level clearly below and Italy's Southern subnation Calabria has a corruption level clearly above the average corruption level in our sample. Cross-country studies, which are based on country averages, fail to capture these within-country differences.

The corruption level is not only heterogeneous within a country, it also tends to cluster in space, i.e., subnations with similar corruption levels neighbor each other. Therefore, in a further step we evaluate the existence of clusters in the spatial arrangement of the subnations' corruption levels. A statistical significant spatial clustering process underlines the importance to take spatial autocorrelation into account as formulated in equation 1. As we assume heterogeneity in the subnations' corruption levels, we calculate a local version of the Moran's I statistics to

[8] See for example La Porta et al. (1999), Paldam (2002), Serra (2006), Seldadyo & de Haan (2006) and Treisman (2007).

Table 1: Summary statistics

	Mean	St.dev	Min	p25	Median	p75	Max
Dependent variable							
Corruption	-0.055	0.739	-5.661	-0.493	-0.117	0.369	2.990
Independent variables							
Log per capita income	8.694	1.231	5.347	7.774	8.759	9.742	11.866
Log population	13.653	1.340	9.900	12.675	13.695	14.599	18.336
Education	7.339	3.227	0.219	5.048	7.733	9.675	14.139
Seaports	0.155	0.509	0	0	0	0	4
Airports	2.218	8.793	0	0	0	1	146
Capital city	0.067	0.251	0	0	0	0	1
Border	0.523	0.500	0	0	1	1	1
Ethnic fractionalization	0.194	0.240	0	0	0.060	0.384	0.849
Autonomous subnation	0.045	0.207	0	0	0	0	1
Log land area	9.351	1.651	4.513	8.231	9.207	10.423	14.656
Terrain ruggedness	1.237	1.255	0	0.272	0.743	1.878	7.751
Log stormrisk	0.482	1.161	0	0	0	0	6.303
Log earthquakerisk	0.466	0.859	0	0	0	0.693	4.543
Precious metals (sites)	100.523	1,134.709	0	0	0	2	29,261
Diamonds (sites)	0.272	4.058	0	0	0	0	128
Oil and gas (sites)	188.654	2,334.873	0	0	0	0	67,796

determine potential local clustering for each of the subnations, individually (Anselin 1995). The local Moran's I is defined as follows:

$$I_i = \frac{(y_i - \bar{y})}{\sigma_y} \sum_{j=1;j\neq i}^{J} \omega_{ij}(y_j - \bar{y}), \tag{2}$$

where I_i expresses for each subnation i the degree of similarity in the corruption level y with its neighboring subnations. The spatial weight matrix ω_{ij} defines the degree of spatial interdependencies between subnation i and j. And σ stands for the standard deviation. Figure 1 shows a graphical representation of the Moran's local index of spatial autocorrelation I_i.

In the so called Moran scatter plot the corruption level of subnation i is plotted on the x-axis and the sum of the spatially lagged corruption levels of the neighbors is plotted on the y-axis. Since the plot is centred on the mean, which is zero, all circles to the right of zero on the x-axis and above zero on the y-axis have a high level of corruption. All circles to the left of zero on the x-axis and below zero on the y-axis have a low level of corruption. The scatter plot is easily decomposed into four quadrants. The upper-right quadrant and the lower-left quadrant correspond to positive spatial autocorrelation meaning neighboring subnations are characterized with similar corruption levels. In contrast, the lower-right and upper-left quadrant correspond to negative spatial autocorrelation meaning neighboring subnations are characterized with dissimilar corruption levels. The clustering of the local Moran's I indices for our sample in the upper-right quadrant and the lower-left quadrant indicates the presence of a positive spatial autocorrelation,

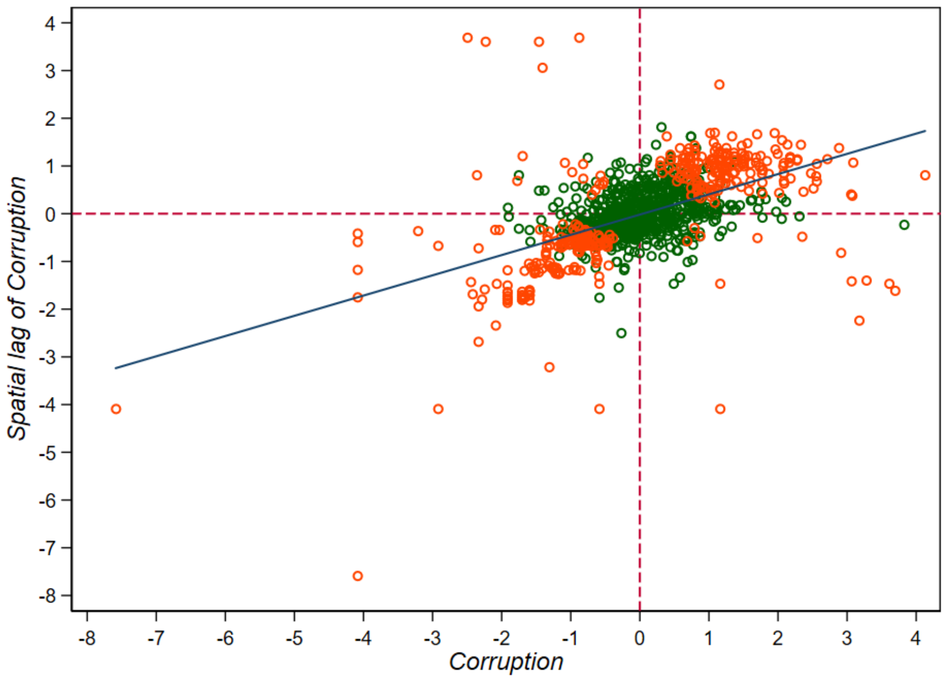

Figure 1: Moran scatter plot on the subnational corruption level

i.e., the subnations' corruption levels are strategic complements.[9] Finally, the slope of the linear fit to the scatter plot equals a global Moran's I of $I = 0.432$ at the highest significance level, which again points to a positive spatial autocorrelation of subnations' corruption levels.

5 The results

Our estimation results are based on specification 1 and on the identification strategy using an instrumental variable estimation approach as described in section 3. Columns (1) and (2) of table 2 present the results of our main model specification. The coefficient of our variable of interest, the spatially lagged level of corruption, ρ, is statistically significant and positive. This implies that the corruption levels of the subnations in our sample are autocorrelated in the way that they are strategic complements. Due to constant economic, cultural and political exchange between the subnations, the corruption level in one subnation is influenced by the corruption levels of neighboring subnations. As a results, corruption levels in a subnation reflects that of its neighbors.

The results for the independent variables are broadly corresponding to previous findings in literature. We find that a subnation's corruption level significantly increases with the size of its population. This is in accordance with the empirical findings in Dong & Torgler (2012) and Limao & Venables (2001) and with the argument put forward in Kelejian et al. (2013) that, because of the logic of collective action, a larger population makes it more difficult to reach workable institutional arrangements, including efficient anti-corruption initiatives.

[9] Local Moran's I indices with a 5% statistically significant clustering process are colored red.

Out of our measures of market integration we find that the corruption level significantly increases with the number of seaports in a subnation and if a subnation is positioned at a national border. Controlling corruption may be more difficult in a complex economic environment. A highly economically integrated subnation may serve as a hub, where citizens are engaged in a greater variety of economic activities and have a higher degree of anonymity. Both may increase the opportunities and the propensity of corruptive acts. We do not find a significant effect on subnational corruption levels for the number of airports and if the subnation comprises a capital city.

The level of corruption in a subnation decreases significantly with land area. This suggests that larger subnations have lower corruption levels than smaller subnations. This finding is in line with Seldadyo & de Haan (2006) and Lopez-Valcarcel et al. (2017), which find that corruption levels increase with population density. Larger subnations are likely to have lower population densities than smaller subnations, which makes citizens of larger subnations less anonymous. Where citizens are not anonymous, the reputation system may serve as an effective informal mechanism to prevent corruption.

We find that the level of corruption increases significantly with the number of mines exploiting precious metals. Subnations with a higher wealth in precious metals also show higher corruption levels. This is in accordance with the "resource curse" argument put forward in previous literature. Increased raw material endowment increases corruption levels as Treisman (2000) shows on a national level. For the other variables capturing natural resource wealth we do not find a statistically significant effect.

We do not find evidence that subnational corruption levels are affected by subnational income levels. This is in line with the findings of Mitton (2016). It seems that the positive relationship between institutions and income, which La Porta et al. (1999) finds on the national level, does not carry over to the subnational level. With regard to our estimates on the cultural factor it shows the expected sign - more ethnic fractionalization resulting in higher corruption level. However, it barely misses the 10% significance level. Likewise, our estimate on subnational political autonomy shows the expected sign and is just significant.

Finally, the economically and statistically significant spatial error implies that not only corruption levels, but also unobserved factors are spatially correlated. This suggests subnations do share common factors captured in the error term that affect their corruption levels.

5.1 Marginal effects

In linear regression models the marginal effects are simply partial derivatives of the dependent variable with respect to the explanatory variables. This arises from linearity and the assumed independence of observations in the model. In spatial regression models the calculation of marginal effects becomes more complicated as the parameter estimates include information from the other observations as well. A change in an independent variable in subnation i will have a direct effect on i's corruption level and an indirect effect on the corruption levels of neighboring subnations, whereby the indirect effect is determined by the spatial dependence structure and incorporates feedback loops. An increase in i's population for example increases i's corruption

Table 2: Estimation results

	Main model		Wealth effect		Corruption effect	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Spatial lag (ρ)	0.534***	(0.086)				
Spatial lag high-middle income (ρ_r)			0.479***	(0.097)		
Spatial lag low-middle income (ρ_p)			0.071	(0.231)		
Spatial lag more corrupt neighbors (ρ_h)					0.086	(0.100)
Spatial lag less corrupt neighbors (ρ_l)					0.150**	(0.068)
Log GDP per capita	−0.034	(0.039)	0.001	(0.080)	−0.051	(0.041)
Log population	0.074***	(0.026)	0.088***	(0.033)	0.095***	(0.034)
Education	0.012	(0.021)	0.015	(0.019)	0.01	(0.022)
Seaports	0.131**	(0.053)	0.126**	(0.054)	0.128**	(0.055)
Airports	0.006	(0.007)	0.007	(0.008)	0.010	(0.008)
Capital city	0.034	(0.069)	−0.020	(0.080)	0.001	(0.071)
Border	0.060*	(0.036)	0.052	(0.034)	0.058*	(0.035)
Ethnic fractionalization	0.121	(0.078)	0.139*	(0.079)	0.160*	(0.088)
Autonomous subnation	−0.150*	(0.094)	−0.157	(0.100)	−0.168*	(0.100)
Log land area	−0.057***	(0.022)	−0.058**	(0.027)	−0.076***	(0.023)
Terrain ruggedness	−0.022	(0.018)	−0.014	(0.021)	−0.029	(0.019)
Log stormrisk	0.050	(0.033)	0.063*	(0.034)	0.072**	(0.035)
Log earthquakerisk	0.016	(0.028)	0.014	(0.031)	0.013	(0.033)
Precious metals	0.054**	(0.023)	0.054**	(0.025)	0.064**	(0.027)
Diamonds	2.891	(2.840)	2.566	(2.613)	2.667	(2.292)
Oil and gas	−0.015	(0.013)	−0.013	(0.016)	−0.023*	(0.013)
Spatial error (λ)	−0.625***	(0.146)	−0.491***	(0.126)	−0.186*	(0.097)
Country fixed effects	Yes		Yes		Yes	
Observations	1,232		1,232		1,232	
R^2	0.563		0.572		0.571	

Notes: Dep. Variable: *Corruption.* *, **, *** indicate 10, 5, 1 % significance levels. Robust standard errors in parenthesis. Spatial weight matrix: inverse distance with 500km distance band; row-normalized. Constant included but not reported.

level in the first place, which produces an increase in neighbor j's corruption levels in the second place, which feeds back to a further increase in subnation i's corruption level in the third place.

The coefficient estimates on the independent variables presented in table 2 constitute the direct effects of changes in i's independent variables on i's corruption level, only. We are, however, interested in the cumulative marginal effects of changes in i's independent variables on i's corruption level, which also include the feedback effects from neighboring subnations. Following LeSage & Pace (2009) and LeSage & Pace (2014) we calculate the cumulative average direct, indirect and total effects from our main model specification 1 for our sample of 1,232 subnations.[10] The results are presented in table 3.

The cumulative average direct effects present the impact on subnation i's corruption level due to changes in subnation i's independent variables. In comparison with the coefficient estimates in table 2, the cumulative direct effects are quantitatively and qualitatively similar. The results confirm that the size of population, the size of land area, a position at the border, the resource

[10] Section A in the appendix gives a formal derivation of the average direct, indirect and total effect in a spatial model.

Table 3: Summary measures on direct, indirect and total effects

	Cumulative effects on *Corruption*					
	Direct effects		Indirect effects		Total effects	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Log GDP per capita	−0.035	(0.040)	−0.037	(0.043)	−0.072	(0.083)
Log population	0.078***	(0.028)	0.081*	(0.045)	0.160**	(0.072)
Education	0.012	(0.022)	0.013	(0.023)	0.025	(0.045)
Seaports	0.138**	(0.056)	0.143*	(0.079)	0.281**	(0.130)
Airports	0.007	(0.008)	0.007	(0.008)	0.013	(0.016)
Capital city	0.036	(0.072)	0.037	(0.074)	0.073	(0.146)
Border	0.063*	(0.036)	0.065	(0.046)	0.128	(0.079)
Ethnic fractionalization	0.128	(0.083)	0.133	(0.104)	0.261	(0.183)
Autonomous subnation	−0.158*	(0.099)	−0.164	(0.116)	−0.322	(0.209)
Log land area	−0.060***	(0.023)	−0.062*	(0.032)	−0.122**	(0.052)
Terrain ruggedness	−0.023	(0.019)	−0.024	(0.021)	−0.047	(0.040)
Log stormrisk	0.052	(0.034)	0.054	(0.038)	0.107	(0.070)
Log earthquakerisk	0.017	(0.030)	0.017	(0.031)	0.034	(0.061)
Precious metals	0.057**	(0.024)	0.059**	(0.030)	0.116**	(0.051)
Diamonds	3.041	(2.978)	3.160	(3.132)	6.202	(6.029)
Oil and gas	−0.016	(0.014)	−0.017	(0.015)	−0.033	(0.028)

Notes: Inferential statistic based on delta-method. *, **, *** indicate 10, 5, 1 % significance levels. Standard errors in parenthesis. 1232 observations. Spatial weight matrix: inverse distance with 500km distance band; row-normalized.

endowments in precious metals as well as the degree of market integration measured by the number of seaports are the main direct subnational determinants of corruption levels. The differences in the coefficient estimates in table 2 and table 3 stem from feedback loops that arise from neighbors influencing neighbors corruption levels, which means that some effects that pass through the neighboring subnations will feedback to further affect the corruption level in the subnation itself.

The cumulative average indirect effects constitute the sum of the impacts that changes in subnation i's independent variables assert on neighboring subnations' corruption levels. The strength of the impact of a change in i's independent variable on neighboring subnations' corruption levels depends on neighboring subnations' positions in space as well as on the degree of connectivity among them, both defined by the spatial weight matrix. Our results suggest that the cumulative average indirect effects are quantitatively and qualitatively similar to the cumulative direct effects for almost all independent variables. This clearly indicates the important role of interdependencies in determining subnational corruption levels.

The cumulative average total effects are the sum of the direct and indirect effects. They constitute the average total impacts from changes in the independent variables of subnation i on the corruption levels of all subnations in our sample including itself. The cumulative average total effects therefore account for the interdependencies within the spatial system. Summing up, our results show that ignoring spatial interdependencies leads to a serious underestimation of the total impacts of changes in independent variables on subnational corruption levels.

5.2 Robustness and sensitivity

We test the consistency of our main results presented in table 2 columns (1) and (2) by conducting several robustness checks. In section 5.2.1, we present the results of estimations based on four alternative definitions of the spatial weight matrix and on one estimation with an alternative normalization form of our main spatial weight matrix. Thereby, we test the sensitivity of our results, if we pose different assumptions on the spatial process. In Section 5.2.2, we address potential endogeneity concerns when using income as an independent variable. Finally, in Section 5.2.3, we tackle the issue of incomplete observations on some neighboring subnations' corruption levels. In all robustness exercises we find that the size and the statistical significance of the spatial interdependency between subnations' corruption levels remain preserved.

5.2.1 Spatial weight matrix alternatives

In line with our argumentation in section 2 and section 3 we are confident that geographic distance is well fitted to capture the strength of the spatial interdependencies and that specification 1 represents the true data-generating process. However, since there is no theoretical guideline on the structure of the spatial process, we construct alternative weight matrices with different definitions of spatial interdependence. First, we calculate a spatial weight matrix using the squared inverse distance between the pairs of subnations that lie within a 500km distance band. This considers a non-linear relationship in the strength of interdependencies. Thereby, closer subnations are given a stronger weight, meaning closer subnations exert stronger influence to each other, and the influence over distance decreases faster. As presented in column (1) in table 4, the spatial lag of the corruption level stays robust with a statistical significant and a slightly smaller coefficient estimate.

Second, we use a nearest neighbor structure to determine the spatial relationship between the subnations. For each subnation i the geographically 8 nearest subnations j are defined as neighbors with spatial influence. These 8 nearest subnations enter the spatial weight matrix with the value $w_{ij} = 1$. All other subnations in the sample are given a value of zero. This weighting alternative gives close subnations a strong homogenous weight, while ignoring the influence of more remote subnations. It has to be noted, that this type of defining spatial interdependencies partly ignores the heterogeneous spatial structure in our sample, i.e., densely clustered regions in some parts of the world and sparse subnational regions in others. Column (2) in table 4 presents the results using this spatial weight matrix. Our parameter of interest, the spatial lag of the level of corruption, again stays robust in size and significance.

Third, we extend the distance band to a radius of 1000km to allow spatial interdependencies across a longer geographic distance. Further, we assume a linear decay in influence as relative distance increases. Column (3) in table 4 shows the results when using this type of spatial weight matrix. Again, the spatial lag of the level of corruption stays statistically significant and positive. We observe a small increase in the size of the spatial lag, which suggests that it is not pure geographic proximity, which influences the degree of spatial interdependencies in subnations' corruption levels. The interdependencies between two subnations may potentially be stronger, if one subnation is hosting a capital city or if one or both subnations show a high degree of market integration, although they are geographically more distant than other neighboring subnations.

Fourth, we use a delaunay triangulation to determine the elements of the spatial weight matrix. The delaunay triangulation determines neighborhood by creating Voronoi triangles from the centroids of the subnations such that each subnation is a triangle node. Nodes connected by a triangle edge are considered neighbors. This type of neighborhood definition gives the natural spatial structure in our sample a stronger consideration and is especially suited for irregular networks, in which distances to nearest neighbors vary significantly. Moreover, it ensures that each subnation has at least one neighbor. The results of using a delaunay triangulation to define the structure of the spatial weight matrix is shown in table 4 column (4). The spatial lag of corruption looses slightly in size, but remains statistically significant at the highest level.

Fifth, we test the sensitivity of our main results with respect to the normalization mode of our spatial weight matrix. As discussed earlier in section 3 row normalizing the spatial weight matrix alters the internal weighting structure, which makes it inferential not neutral. To give consideration to this issue, we follow Kelejian & Prucha (2010*b*) and divide the elements w_{ij} by the absolute value of the largest eigenvalue ν of the matrix. This type of normalization, which is also known as spectral normalization, has the advantage that it removes any measure-unit effects, but preserves relations between rows. However, spectral normalization makes computation and interpretation of spillover effects more complicated, which is the reason why we prefer a row normalization in our main spatial weight matrix. Again, our parameter of interest, the spatial lag of corruption, remains highly significant and positive (see column (5) in table 4). However, it has to be noted that with spectral normalization the magnitude of our spatial lag estimate lies on the higher range of the admissible parameter space defined as $(-\frac{1}{\nu}, \frac{1}{\nu})$, which makes the interpretation of this estimate problematic.

5.2.2 Controlling for malaria instead of income

Clague, Keefer, Knack & Olson (1996) and La Porta et al. (1999) find a significant negative relationship between income and corruption. They argue that an increase in income enables to channel more resources into controlling corruption and, therefore, reduce corruption levels. The causal relationship may, however, also run the other direction. A decrease in the corruption level may lead to an increase in income. This potential simultaneity can make a causal interpretation of specification 1 problematic. To account for this issue, we test whether the coefficient estimate of the spatial lag changes when we either completely omit subnational per capita income from the regression or replace it by a historical proxy. Columns (1) and (2) of table 5 present the results when subnational per capita income is omitted as an independent variable. In columns (3) and (4) we replace subnational per capita income with a measure of historic risk of malaria infection. The historical prevalence of malaria in world regions has influenced historical population densities and settler strategies. Literature finds that in areas, where malaria risk was high, less extractive institutions were set up. This enabled a better economic development that lasts until present day (Acemoglu & Johnson 2005). Unlike income, historical malaria risk is clearly exogenous to nowadays corruption levels. For that reason malaria risk has become

Table 4: Alternative spatial weight matrices

	(1)	(2)	(3)	(4)	(5)
Spatial lag (ρ)	0.498***	0.518***	0.613***	0.470***	1.190***
	(0.086)	(0.090)	(0.121)	(0.076)	(0.266)
Log GDP per capita	−0.040	−0.030	−0.017	−0.024	−0.056
	(0.039)	(0.039)	(0.041)	(0.039)	(0.043)
Log population	0.074***	0.084***	0.074***	0.077**	0.094***
	(0.026)	(0.030)	(0.023)	(0.033)	(0.033)
Education	0.010	0.008	0.010	0.001	0.006
	(0.020)	(0.020)	(0.021)	(0.021)	(0.023)
Seaports	−0.134**	−0.123**	−0.121**	−0.116**	−0.122**
	(0.055)	(0.052)	(0.053)	(0.052)	(0.056)
Airports	0.006	0.012*	0.009	−0.012	−0.012
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Capital city	0.036	0.025	0.015	0.033	0.036
	(0.070)	(0.070)	(0.068)	(0.073)	(0.071)
Border	0.058*	0.060*	0.062*	0.053*	0.045
	(0.033)	(0.033)	(0.034)	(0.032)	(0.034)
Ethnic fractionalization	0.123	0.131*	0.114	0.107	0.158*
	(0.079)	(0.082)	(0.076)	(0.086)	(0.091)
Autonomous subnation	−0.148*	−0.150*	−0.118	−0.144	−0.206**
	(0.092)	(0.086)	(0.089)	(0.091)	(0.096)
Log land area	−0.055***	−0.061***	−0.057***	−0.058**	−0.075***
	(0.021)	(0.022)	(0.022)	(0.023)	(0.024)
Terrain ruggedness	−0.019	−0.023*	−0.024	−0.021	−0.027
	(0.018)	(0.017)	(0.018)	(0.017)	(0.019)
Log stormrisk	0.052	0.061*	0.053	0.055*	0.073**
	(0.032)	(0.031)	(0.033)	(0.030)	(0.037)
Log earthquakerisk	0.0015	0.030	0.015	0.019	0.013
	(0.029)	(0.027)	(0.029)	(0.026)	(0.032)
Precious metals	0.056**	0.066***	0.053**	0.055**	0.066**
	(0.023)	(0.021)	(0.023)	(0.025)	(0.029)
Diamonds	2.934	2.595	2.686	2.421	2.781
	(2.820)	(2.421)	(2.055)	(2.131)	(2.269)
Oil and gas	−0.015	−0.029**	−0.022	−0.025**	−0.023*
	(0.014)	(0.011)	(0.012)	(0.012)	(0.014)
Spatial error (λ)	−0.562***	−1.012***	−0.726***	0.708***	0.200
	(0.129)	(0.257)	(0.223)	(0.158)	(0.749)
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,232	1,232	1,232	1,232	1,232
R^2	0.562	0.562	0.570	0.558	0.557

Notes: Dep. Variable: *Corruption.* *, **, *** indicate 10, 5, 1 % significance levels. Robust standard errors in parenthesis. Alternative spatial weight matrices; all row-normalized except for specification (5) where the baseline spatial weight matrix is spectral-normalized. Constant included but not reported.

a very appealing instrument broadly used in instrumental variable regression analysis on the determinants of institutional and economic development (Gooch, Martinez-Vazquez & Yedgenov 2016).

The regression results presented in table 5 show that the coefficient estimates on the spatial lag remain robust in economic and statistical significance when we take care of the endogeneity issue between income and corruption levels. There is almost no change in the coefficient estimates when we either omit subnational per capita income or replace subnational income by subnational malaria risk.

Table 5: Estimate without GDP per capita and with malaria risk

(1)	**Excl. GDPpc**		**Malaria risk**	
	Coefficient	SE	Coefficient	SE
Spatial lag (ρ)	0.556***	(0.091)	0.557***	(0.090)
Malaria risk			−0.409	(0.274)
Log GDP per capita				
Log population	0.073***	(0.025)	0.073***	(0.025)
Education	0.005	(0.020)	0.004	(0.020)
Seaports	0.131**	(0.053)	0.129**	(0.053)
Airports	0.006	(0.007)	0.006	(0.007)
Capital city	0.027	(0.067)	0.026	(0.067)
Border	0.059*	(0.034)	0.060*	(0.034)
Ethnic fractionalization	0.119	(0.077)	0.128*	(0.077)
Autonomous subnation	−0.153*	(0.095)	−0.152	(0.095)
Log land area	−0.055**	(0.022)	−0.053**	(0.022)
Terrain ruggedness	−0.019	(0.018)	−0.020	(0.019)
Log stormrisk	0.050	(0.033)	0.052	(0.033)
Log earthquakerisk	0.015	(0.028)	0.014	(0.028)
Precious metals	0.053**	(0.023)	0.054**	(0.023)
Diamonds	2.785	(2.858)	2.870	(2.849)
Oil and gas	−0.015	(0.013)	−0.015	(0.013)
Spatial error (λ)	−0.654***	(0.156)	−0.654***	(0.156)
Country fixed effects	Yes		Yes	
Observations	1,232		1,232	
R^2	0.5609		0.5615	

Notes: Dep. Variable: *Corruption*. *, **, *** indicate 10, 5, 1 % significance levels. Robust standard errors in parenthesis. Spatial weight matrices: inverse distance matrix with 500km distance band; row-normalized. Constant included but not reported.

5.2.3 Estimation using a subsample with no missing bordering neighbors

It is evident from equation 1 that the calculation of the spatial lag for each subnation requires observations on the dependent as well as independent variables for all subnations. A fraction of these observations is not available. Although, Kelejian et al. (2013) show that the consistency of the coefficient estimate of the spatial lag is unaffected by the omission of a wide class of spatially-correlated explanatory variables, we still want to address this issue by implementing an estimation procedure suggested by Kelejian & Prucha (2010*a*), which explicitly takes the structure of missing data into account.

We group the 1,232 subnations in our sample into two mutually exclusive and exhaustive sets. In the first set, containing $s_1 = 1, 2, 3, ..., 838$ subnations, the dependent variable as well as all independent variables are fully observed. We refer to this set of 838 subnations, which also includes observations on the corruption levels for all directly bordering subnations, as the core set. In the second set, containing $s_2 = 1, 2, 3, ..., 394$ subnations, the level of corruption and all independent variables are observed for the subnations themselves, but for some directly bordering neighbors data on corruption levels is missing. We refer to this set of 394 subnations as edge set.

Based on this setting, we specify a spatial model as stated in equation 3, which directly accounts for the incomplete dataset.

$$\begin{aligned} y_{ic,1} &= \rho \sum_{j=1}^{J} (\omega_{ij} y_{j,1} + \varpi_{ij} y_{j,2}) + X_{i,1}\beta_1 + \theta_{c,1} + \mu_{ic,1} \\ \mu_{ic,1} &= \lambda \sum_{j=1}^{J} (\omega_{ij} \mu_{j,1} + \varpi_{ij} \mu_{j,2}) + \varepsilon_{ic,1}, \end{aligned} \tag{3}$$

where the subindex 1 refers to the core set in our sample, i.e., these subnations, which are fully observed, and subindex 2 refers to the edge set, i.e., subnations for which observations on the corruption level for some directly bordering neighbors is missing. Further, ω_{ij} are the elements of the spatial weight matrix, which relate to the core group. ϖ_{ij} covers the elements of the spatial weight matrix for the edge group.

Following Kelejian & Prucha (2010*a*) we first estimate equation 3 by two-stage least squares and use the subnation-specific independent variables $X_{i,1}$ of the core set and their spatial lags ωX_{i1} as instruments for $y_{j,1}$. This method provides consistent parameter estimates. We estimate $\mu_{ic,1}$ from equation 3 and determine the parameter λ by applying the GMM procedure as proposed in Kelejian & Prucha (1999) with setting $\varpi_{ij}\mu_{j,2} = 0$.[11] Lastly, we use the estimate of λ to transform the model via a spatial variant of the Cochrane-Orcutt procedure to estimate the resulting model by two-stages least squares.

The estimation results of this procedure are reported in table 6. The coefficient estimate of the spatial lag of corruption remains robust, slightly higher, and at the highest significance level. The estimates of the independent variables remain largely robust. This indicates that the results of our baseline estimation presented in table 2 are not strongly biased by potential missing observation issues.

[11] We assume for the purposes of large sample results that as we move towards infinity $s_2/s_1 \longrightarrow 0$. This is reasonable since s_2 is smaller than s_1, which makes the term $\varpi_{ij}\mu_{j,2}$ asymptotically negligible. For a more detailed discussion on this procedure see Kelejian & Prucha (2010*a*).

Table 6: Estimates with restricted sample

(1)	No Missing	
	Coefficient	SE
Spatial lag (ρ)	0.582***	(0.083)
Log GDP per capita	−0.007	(0.041)
Log population	0.054**	(0.025)
Education	−0.016	(0.021)
Seaports	0.148***	(0.045)
Airports	0.010*	(0.005)
Capital city	0.050	(0.078)
Border	0.000	(0.046)
Ethnic fractionalization	0.186**	(0.081)
Autonomous subnation	0.100	(0.086)
Log land area	−0.065**	(0.030)
Terrain ruggedness	−0.035**	(0.017)
Log stormrisk	0.075***	(0.028)
Log earthquakerisk	0.021	(0.031)
Precious metals	0.047**	(0.020)
Diamonds	−3.432	(13.486)
Oil and gas	−0.037***	(0.009)
Spatial error (λ)	−0.841*	(0.502)
Country fixed effects	Yes	
Observations	838	
R^2	0.851	

Notes: Dep. Variable: *Corruption*. *, **, *** indicate 10, 5, 1 % significance levels. Robust standard errors in parenthesis. Spatial weight matrices: inverse distance matrix with 500km distance band; row-normalized. Constant included but not reported. Estimates are based on subsample of subnations with no missing observations in their contiguous neighborhood.

5.3 Asymmetric effects

The degree of connectivity between two subnations and their position in space determine how changes in one subnation's corruption level disseminate to neighboring subnations. Recent literature implies that the degree of connectivity is not homogenous between countries, but depends on, for example, the level of economic development (Borsky & Raschky 2015) or on the level of institutional quality (Kelejian et al. 2013). Therefore, in the second part of our empirical analysis we investigate whether the strength of spatial interdependency in corruption levels is different for different groups of subnations. To do this, we extend the spatial model as laid out in specification 1 and allow for asymmetric effects, which depend on the characteristics of subnations. In section 5.3.1, we study whether a subnation's economic development status alters the potential to disseminate corruption across space. In section 5.3.2, we study whether a subnation's corruption level relative to its neighboring subnations impacts the strength of the spatial impact.

5.3.1 The absolute wealth effect

Splitting our sample into two subsamples according to their income level, we can see that subnations with a high-middle income differ from subnations with a low-middle income in their mean level of corruption and a number of independent variables.[12] As discussed and exemplified in section 2 the strength of subnations' spatial interdependencies in corruption levels depends on their degree of connectivity and, hence, the extent of their economic, political and sociocultural exchange. There is a broad literature dealing with the relationship between countries' economic development and international integration. In general, they find that countries with high economic growth exhibit a high degree of trade openness (see Edwards 1998, Harrison 1996, Frankel & Romer 1999, Irwin & Terviö 2002). With regard to sociocultural exchange, it is in particular subnations with higher income level that attract immigration flows. Finally, as shown in Borsky & Raschky (2015) on the country level, subnations with a higher level of economic development often play a stronger role in the exchange of regulatory standards in a region. For this higher level of exchange we expect that changes in the corruption levels of high-middle income subnations disseminate more strongly in space than changes in the corruption levels of low-middle income subnations. We extend the main model 1 as follows

$$
\begin{aligned}
y_{ic} &= \rho_r \sum_{j=1}^{J} \omega_{ij}^{r} y_j + \rho_p \sum_{j=1}^{J} \omega_{ij}^{p} y_j + X_i\beta + \theta_c + \mu_{ic} \\
\mu_{ic} &= \lambda \sum_{j=1}^{J} \omega_{ij}\mu_j + \varepsilon_{ic},
\end{aligned}
\tag{4}
$$

where ω^r is a row-normalized spatial weight matrix, where each element $\omega_{ij}^r = \frac{1}{d_{ij}}$ only if subnation i is characterized by a high-middle income and if subnations i and j are within a geographic neighborhood of 500km, and 0 otherwise. ω^p is a row-normalized spatial weight matrix, where each element $\omega_{ij}^p = \frac{1}{d_{ij}}$ only if subnation i is characterized by a low-middle income and if subnations i and j are within a geographic neighborhood of 500km, and 0 otherwise. We estimate the model by the previously described instrumental variable procedure using the subnation specific independent variables X_i and their spatial lags $W^r X_i$ and $W^p X_i$, which are differentiated for rich and poor subnations, as instruments for y_j.

Table 2 columns (3) and (4) contain the results on the absolute wealth effect. The coefficient estimate ρ_r, which measures the spatial impact of subnations with a high-middle income, is large in size, statistically significant and captures almost all of the total spatial interdependency measured in our main specification and presented in columns (1) and (2). The coefficient estimate ρ_p, which measures the spatial impact of subnations with a low-middle income, is small in size and statistically insignificant. The difference between the spatial impacts of these two groups of subnations points at the importance of the degree of connectivity among subnations, i.e., the

[12] Following the World Bank Analytical Country Classification in the year 2005, we categorize subnations with a GDP per capital $\geq$ 3,466\$ as high-middle income subnations and subnations with a GDP per capital $<$ 3,466\$ as low-middle income subnations. Table B8 in the appendix compares the mean values and standard deviations of the variables for the two subsamples.

potential channels of economic, political and sociocultural exchange, to disseminate corruption levels in space. Wealthier subnations are more strongly connected and, therefore, have a greater influence on the corruption levels of neighboring subnations.

5.3.2 The relative corruption level effect

Following Kelejian et al. (2013), we investigate whether the strength of the spatial impact varies, if subnation i has a higher or lower corruption level as compared to the average of its neighboring subnations j. Differences in relative corruption levels may influence the strength of the diffusion. It may be easier to learn how to control corruption from less rather than more corrupt neighbors. Governments of less corrupt neighboring subnations may deliver best-practices for setting up effective anti-corruption initiatives. Business partners operating in less corrupt neighboring subnations may push to decrease corruption levels in the host subnation to reduce costs, uncertainties and risks. People emigrating from less corrupt subnations may spread their beliefs, understandings and knowledge on a sound way of organizing interactions, which contributes to a less corrupt behaviour in the destination subnation. To account for this, we extend the model as specified in equation 1 as follows

$$\begin{aligned} y_{ic} &= \rho_h \sum_{j=1}^{J} \omega_{ij}^h y_j + \rho_l \sum_{j=1}^{J} \omega_{ij}^l y_j + X_i\beta + \theta_c + \mu_{ic} \\ \mu_{ic} &= \lambda \sum_{j=1}^{J} \omega_{ij}\mu_j + \varepsilon_{ic}, \end{aligned} \tag{5}$$

where ω^h is a row-normalized spatial weight matrix, for which each element $\omega_{ij}^h = \frac{1}{d_{ij}}$ if $y_i \geq y_j$ and subnations i and j are within a geographic neighborhood of 500km, and 0 otherwise. Whereas, ω^l is a row-normalized spatial weight matrix, where each element $\omega_{ij}^l = \frac{1}{d_{ij}}$ if $y_i < y_j$ and subnations i and j are within a geographic neighborhood of 500km, and 0 otherwise. Again, we estimate the model by the previously described instrumental variable procedure using the subnation specific independent variables X_i and the spatial lags W^hX_i and W^lX_i, which are differentiated for subnations with a high and low level of corruption, as instruments for y_j.

Table 2 columns (5) and (6) show the results on this empirical exercise. We find a positive and statistically significant spatial impact from neighbors with relatively lower corruption levels. The spatial impact of relatively more corrupt neighbors is half the size of relatively less corrupt neighbors and insignificant. This implies that relative corruption levels do play a role for the spatial diffusion of corruption. Subnations with a relatively low corruption level exert more influence on neighboring subnations' corruption levels.

6 Conclusions

The level of corruption differs not only between countries but also between subnations within countries. Moreover, corruption levels are not randomly distributed, they tend to cluster in space. This paper discusses causes and provides empirical evidence for this spatial phenomena, which helps to get a better understanding of the determinants of corruption. Our main argument is that the level of corruption in one subnation is not only determined by nation-specific factors and its own characteristics, but it also depends on the corruption level of neighboring subnations. We extend the existing literature on spatial institutional interdependence by analyzing a large dataset of corruption levels of 1,232 subnations in 81 countries. To do this, we draw back on subnational institutions data collected by Mitton (2016) and construct an index variable, which measures the perceived corruption level in a subnation. To determine the strength of interdependencies between the subnations' corruption levels, we base our analysis on a generic spatial model and apply an instrumental variable procedure that accounts for the spatial autocorrelation in both the dependent variable and in the error term.

Our results indicate that a subnation's corruption level is significantly affected by the corruption levels of its neighboring subnations. Spatial interdependency and feedback effects stemming from a marginal change in an independent variable are about the same size as direct effects. This means, that the total impact of a marginal change in an independent variable is about twice as large as what the coefficient estimate on this independent variable would suggest, if a conventional model ignoring spatial effects was specified. This underlines the importance of taking the effect of spatial interdependencies into account when analyzing total impacts of policy measures to reduce the level of corruption. As we extend our baseline model to allow for heterogeneous spatial impacts, we find that in particular high-middle income subnations tend to spill in space. From this result we infer that the potential to spill in space lies in subnations' degree of connectivity. It is the high-middle income subnations, which are more connected via economic, sociocultural and political exchange. Moreover, we find that subnations with a relative low corruption level have a stronger spatial impact on their neighboring subnations than subnations with a relative high corruption level. This is in line with Kelejian et al. (2013), which implies that it might be easier to adopt better examples, i.e., lower corruption levels, as worse ones.

Our findings have important policy implications for anti-corruption initiatives. Since federal and regional budgets are constraint and widespread institutional policies may be difficult to implement, the design of economically efficient institutional development policies should consider the impact of spatial interdependencies in subnational corruption levels. Estimates of the impacts of anti-corruption initiatives, that do not consider the effects of spatial interdependencies, are downward biased. Concentrating measures to decrease corruption in countries' hubs can yield substantial spillover effects on corruption levels of other subnations. Such hubs are subnations characterized by a high degree of connectivity, such as capital city subnations, highly market integrated subnations or border subnations. Under certain circumstances it can be difficult to implement effective anti-corruption initiatives in a subnation, area of subnations or even country. This can, for example, be due to weak institutions in place. Spatial interdependencies between subnations, however, may help to circumvent this issue. Setting up appropriate measures to battle corruption in subnations that are in extensive economic, political or sociocultural exchange with others, may indirectly affect corruption levels in subnations or countries with a low quality of institutions. Our findings underscore the relevance of coordinating subnational anti-corruption efforts through regional agreements as proposed in Dong & Torgler (2012).

Our study has two limitations we shortly want to discuss. First, it has to be noted that the preferred way to measure corruption would be by direct observation. Due to corruption's secretive nature this is obviously difficult. Our measure for subnational corruption levels is based on perceptions, which has some drawbacks. Respondents in different countries may respond differently to questions, because of variation in societal norms. We address this issue by controlling for cross-country cultural differences in our estimations, but cannot account for within-country variations in societal norms. Second, we base our study on a cross-sectional dataset. Therefore, we can not account for the temporal impacts of a change in corruption levels. The evolution of corruption, however, is a path-dependent process where present corruption levels are dependent on past corruption levels. In our opinion, both analyzing spatial interdependencies in observed corruption levels and extending the dataset over multiple time periods would be an interesting expansion for future studies as data on observed corruption levels over time gets more available (see Fazekas & Kocsis 2017).

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Appendix

A Marginal effects

To derive the direct and indirect impact we follow LeSage & Pace (2009). The data-generating process is given as

$$y_{ic} = (I - \rho W)^{-1}(X_{ic}\beta + \theta_c + \mu_{ic}), \tag{6}$$

where

$$(I_n - \rho W)^{-1} = I_n + \rho W + \rho^2 W^2 + \dots.$$

We rewrite part of equation 6 as

$$\begin{aligned}(I_n - \rho W)^{-1} X\beta &= \sum_{r=1}^{k} (I_n - \rho W)^{-1} x_r \\ &= S_r(W) x_r.\end{aligned}$$

where r stands for the independent variables. Following LeSage & Pace (2009) and Kim, Phipps & Anselin (2003) the data-generating process can then be rewritten as

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \sum_{r=1}^{k} \begin{pmatrix} Sr(W)_{11} & Sr(W)_{12} & \dots & Sr(W)_{1n} \\ Sr(W)_{21} & Sr(W)_{22} & \dots & Sr(W)_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ Sr(W)_{n1} & Sr(W)_{n2} & \dots & Sr(W)_{nn} \end{pmatrix} \begin{pmatrix} x_{1r} \\ x_{2r} \\ \vdots \\ x_{nr} \end{pmatrix} + (I_n - \rho W)^{-1}\epsilon. \tag{7}$$

It follows that unlike the case of the independent data model, the derivative of y_i with respect to x_r is potentially non-zero, taking a value determined by the i, j^{th} element of the matrix $S_r(W)$. It can be divided into a direct effect and an indirect effect. The direct effect for subnation i captures the impact of a change in an independent variable x_{ir} on its own level of corruption and is given by

$$\frac{y_i}{x_{ir}} = S_r(w)_{ii}.$$

This impact includes the effect of feedback loops, where observation i affects observation j and observation j also affects observation i as well as longer paths, which might go from observation i to j to k and back to i. The indirect effect measures the impact of a change in another subnations' independent variable on subnation i's corruption level. It implies that a change in the independent variable of one subnation has a potential impact on the corruption level on all other subnations. This is a logical consequence of introducing Wy as an right-hand side variable in the model. The indirect effect is defined as

$$\frac{y_i}{x_{jr}} = S_r(w)_{ij}.$$

Consequently, every diagonal elements of $S_r(W)$ represents a direct effect and every off-diagonal elements of $S_r(W)$ represent indirect impacts of a change in an independent variable x_r. The size of the impact differs over all subnations and depends on its position in space and the degree of connectivity with the other subnations both determined by the spatial weighting matrix, the parameter ρ standing for the degree of spatial interdependencies in corruption level, and the parameter β. Following LeSage & Pace (2009) and LeSage & Pace (2014) these effects can be summarized using scalar measures given by

$$\begin{aligned}\overline{M}(r)_{direct} &= n^{-1}tr(S_r(W))\\ \overline{M}(r)_{total} &= n^{-1}\iota_n' S_r(W)\iota_n \\ \overline{M}(r)_{indirect} &= \overline{M}(r)_{total} - \overline{M}(r)_{direct}\end{aligned} \tag{8}$$

where tr stands for the trace of the matrix and ι_n is a $n \times 1$ vector of ones. $\overline{M}(r)_{direct}$ is the cumulative average direct effect, which is the average value of the diagonal of $S_r(W)$. $\overline{M}(r)_{total}$ stands for the cumulative average total effect of a change in the r_{th} independent variable of a subnation on the corruption level of all subnations in our sample including itself. It is the average of all column sums of $S_r(W)$. Finally, $\overline{M}(r)_{indirect}$ stands for the cumulative indirect impact and is by definition the difference between the cumulative average total impact and the cumulative average direct impact. Formally, the cumulative average indirect impact is the average column sum of the off-diagonal elements in $S_r(W)$.

B Tables

Table B1: Sample composition

Country	Obs.	Type	Level	Country	Obs.	Type	Level
Albania	8	Counties	ADM1	Macedonia	8	Statistical reg.	NUTS3
Argentina	22	Provinces	ADM1	Malaysia	6	States	ADM1
Austria	9	States	NUTS2	Mexico	31	Statistical reg.	ADM1
Bangladesh	7	Divisions	ADM1	Mongolia	20	Aimags	ADM1
Belarus	7	Regions	ADM1	Montenegro	4	Regions	ADM1
Belgium	11	Provinces	NUTS2	Mozambique	11	Provinces	ADM1
Benin	12	Departments	ADM1	Nepal	4	Regions	ADM1
Bolivia	9	Departments	ADM1	Netherlands	12	Provinces	NUTS2
Bosnia Herzegovina	10	Cantons	ADM1	Niger	2	Departments	ADM1
Brazil	24	States	ADM1	Nigeria	31	States	ADM1
Bulgaria	28	Planning reg.	NUTS3	Pakistan	5	Provinces	ADM1
Burkina Faso	45	Provinces	ADM1	Panama	9	Provinces	ADM1
Canada	12	Provinces	ADM1	Paraguay	15	Departments	ADM1
Chile	13	Regions	ADM1	Peru	23	Regions	ADM1
Colombia	27	Departments	ADM1	Philippines	16	Regions	ADM1
Congo, Dem. Rep.	4	Provinces	ADM1	Poland	16	Provinces	NUTS2
Croatia	20	Counties	NUTS3	Portugal	7	Statistical reg.	NUTS2
Czech Republic	14	Regions	NUTS3	Romania	42	Departments	NUTS3
Denmark	5	Regions	NUTS2	Russian Fed.	20	Fed. Subjects	ADM1
Dominican Republic	31	Provinces	ADM1	Senegal	10	Regions	ADM1
Ecuador	21	Provinces	ADM1	Serbia	4	Statistical reg.	ADM1
El Salvador	14	Departments	ADM1	Slovakia	8	Regions	NUTS3
Estonia	5	Statistical reg.	NUTS3	Slovenia	12	Statistical reg.	NUTS3
France	26	Regions	NUTS2	South Africa	9	Provinces	ADM1
Gambia	2	Divisions	ADM1	Spain	17	Auton. com.	NUTS2
Georgia	5	Regions	ADM1	Sri Lanka	9	Provinces	ADM1
Germany	16	States	NUTS2	Swaziland	2	Regions	ADM1
Greece	13	Peripheries	NUTS2	Sweden	21	Provinces	NUTS3
Guatemala	22	Departments	ADM1	Tanzania	21	Regions	ADM1
Honduras	18	Departments	ADM1	Turkey	16	Sub-regions	NUTS2
Hungary	20	Counties	NUTS3	Uganda	4	Admin. regions	ADM1
Indonesia	9	Provinces	ADM1	Ukraine	27	Oblast	ADM1
Italy	21	Regions	NUTS2	United Kingdom	37	Statistical reg.	NUTS2
Kazhakstan	16	Provinces	ADM1	United States	49	States	ADM1
Kenya	8	Provinces	ADM1	Uruguay	19	Departments	ADM1
Kosovo	7	Municipalities	ADM1	Uzbekistan	5	Regions	ADM1
Kyrgyzstan	6	Regions	ADM1	Venezuela	22	States	ADM1
Lao PDR	4	Provinces	ADM1	Vietnam	63	Provinces	ADM1
Latvia	5	Planning reg.	NUTS3	Zambia	9	Provinces	ADM1
Lesotho	10	Districts	ADM1	Zimbabwe	10	Provinces	ADM1
Lithuania	10	Counties	NUTS3				

Table B2: Questions from *Afrobarometer survey* entering *Corruption*

Number	Question	Min	Max	Direction
56C	How many elected local government councilors do you think are involved in corruption?	0	3	+
56E	How many local government officials do you think are involved in corruption?	0	3	+
56F	How many of the police do you think are involved in corruption?	0	3	+
56H	How many judges and magistrates do you think are involved in corruption?	0	3	+
57A	In the past year, how often have you had to pay a bribe to get a document or permit?	0	3	+
57B	In the past year, how often have you had to pay a bribe to get a child into school?	0	3	+
57C	In the past year, how often have you had to pay a bribe to get a household service?	0	3	+
57D	In the past year, how often have you had to pay a bribe to get medical attention?	0	3	+
57E	In the past year, how often have you had to pay a bribe to avoid a problem with police?	0	3	+

Notes: The table reports the questions extracted from the *Afrobarometer survey* to be used in the calculation of *Corruption* as subnational measures on corruption in African countries. Min and Max indicate the range of possible responses. Direction indicates whether a higher response indicates more corruption (+) or less corruption (-). Data are taken from 17,950 individuals surveyed in 2005. Data for Burkina Faso come from 2008 and include a subset of the questions listed.

Table B3: Questions from *Latin American Public Opinion Project* entering *Corruption*

Number	Question	Min	Max	Direction
EXC2	Has any police official asked you for a bribe in the last year?	No	Yes	+
EXC6	During the last year has any public official asked you for a bribe?	No	Yes	+
EXC7	Based on your own experience, do you believe corruption among public officials is common?	1	4	-
EXC11	During the last year have you had to pay a bribe to process a document with the municipality?	No	Yes	+
EXC14	Have you had to give a bribe to the courts in the last year?	No	Yes	+
EXC15	Have you had to give a bribe to obtain public health services in the last year?	No	Yes	+
EXC16	Have you had to give a bribe at your child's school in the last year?	No	Yes	+
EXC17	Has anyone asked you for a bribe to avoid having the electricity turned off	No	Yes	+
N9	To what extent would you say the current government combats government corruption?	1	7	-

Notes: The table reports the questions extracted from the *Latin American Public Opinion Project* to be used in the calculation of *Corruption* as subnational measures on corruption in the Americas. Min and Max indicate the range of possible responses. Direction indicates whether a higher response indicates more corruption (+) or less corruption (-). Data are taken from 27,650 individuals surveyed in 2006. Data for Argentina come from 2008 and include a subset of the questions listed. Data from the U.S. and Canada also include a subset of the questions listed.

Table B4: Questions from *Asia Foundation survey* entering *Corruption*

Country	Question	Min	Max	Direction
Bangladesh	Informal charges	0	10	-
Malaysia	Informal charges	0	10	-
Nepal	Informal charges	3	12	-
Philippines	Corruption prevention	5	20	-
Sri Lanka	Informal charges, favoritism, and discrimination	0	9	-
Vietnam	Informal charges	0	10	-

Notes: The table reports the questions extracted from the *Asia Foundation survey* to be used in the calculation of *Corruption* as subnational measures on corruption in Asian countries. Min and Max indicate the range of possible responses. Sub-indices are created by the survey sponsors except for Nepal, the Philippines, and Thailand, where the sub-indices from available survey questions are aggregated and named by Mitton (2016). Direction indicates whether a higher response indicates more corruption (+) or less corruption (-). Data are taken from 31,903 firms and individuals surveyed between 2006 and 2011.

Table B5: Questions from *Quality of Government Institute survey* entering *Corruption*

Question	Min	Max	Direction
How likely is it the corruption by a public employee or politician would be exposed by the local mass media?	0	10	-
Does the police force give special advantages to certain people in your area?	0	10	-
In the past 12 months has anyone in your household paid a bribe to health or medical services?	Yes	No	-
Do you agree that corruption is prevalent in the police force in your area?	0	10	-
Do you agree that corruption is prevalent in your area's local public school system?	0	10	-
Do you agree that corruption is prevalent in the public health care system in your area?	0	10	-

Notes: The table reports the questions extracted from the *Quality of Government Institute survey* to be used in the calculation of *Corruption* as subnational measures on corruption in European countries. Min and Max indicate the range of possible responses. Direction indicates whether a higher response indicates more corruption (+) or less corruption (-). Data are taken from 33,540 individuals surveyed between 2009 and 2010.

Table B6: Questions from *Latinobarómetro survey* entering *Corruption*

Number	Question	Min	Max	Direction
P82STB	Has anyone in your family known of an act of corruption in the last 12 months?	Yes	No	+
P84ST	If the total number of public employees were 100, how many would you say are corrupted?	0	100	-

Notes: The table reports the questions extracted from the *Latinobarómetro survey* to be used in the calculation of *Corruption* as subnational measures on corruption in Latin American countries. Min and Max indicate the range of possible responses. Direction indicates whether a higher response indicates more corruption (+) or less corruption (-). Data are taken from 20,222 individuals surveyed in 2005.

Table B7: Questions from *World Bank Enterprise Survey* entering *Corruption*

Number	Question	Min	Max	Direction
C5	Was an informal gift or payment expected or requested for an electrical connection?	Yes	No	-
C14	Was an informal gift or payment expected or requested for a water connection?	Yes	No	-
C21	Was an informal gift or payment expected or requested for a telephone connection?	Yes	No	-
G4	Was an informal gift or payment expected or requested for a construction-related permit?	Yes	No	-
J1B	Do you agree that it is common to pay informal payments or gifts to get things done?	1	4	+
J5	In meetings with tax officials was a gift or informal payment expected or requested?	Yes	No	-
J6	In dealing with government, what percent of contract value is paid in informal payments to secure the contract?	0	NA	+
J7A	What percent of annual sales would be paid in informal payments or gifts to public officials to "get things done"?	0	NA	+
J12	Was an informal gift or payment expected or requested for an import license?	Yes	No	-
J15	Was an informal gift or payment expected or requested for an operating license?	Yes	No	-
J30F	How much of an obstacle is corruption to the operations of this establishment?	0	4	+

Notes: The table reports the questions extracted from the *World Bank Enterprise Survey* to be used in the calculation of *Corruption* as subnational measures on corruption around the world. Min and Max indicate the range of possible responses. Direction indicates whether a higher response indicates more corruption (+) or less corruption (-). Data are taken from 40,792 firms surveyed between 2006 and 2011.

Table B8: Descriptive statistics rich versus poor subnations

	Full Sample		**High-middle income**		**Low-middle income**	
	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
Dependent Variable						
Corruption	0.055	0.739	−0.252	0.811	0.105	0.631
Independent variables						
Log per capita income	8.694	1.231	9.661	0.696	7.905	0.986
Lop population	13.653	1.340	13.750	1.270	13.580	1.391
Education	7.339	3.227	9.388	2.053	5.665	3.041
Seaports	0.155	0.509	0.291	0.694	0.044	0.226
Airports	2.218	8.793	4.273	12.770	0.540	1.083
Capital City	0.067	0.251	0.065	0.247	0.069	0.254
Border	0.523	0.500	0.534	0.499	0.513	0.500
Ethnic fractionalization	0.194	0.240	0.115	0.178	0.259	0.263
Autonomous subnation	0.045	0.207	0.070	0.256	0.024	0.152
Log land area	9.351	1.651	9.536	1.617	9.199	1.664
Terrain Ruggedness	1.237	1.255	1.146	1.166	1.311	1.320
Log stormrisk	0.482	1.161	0.450	1.227	0.509	1.104
Log earthquakerisk	0.466	0.859	0.454	0.870	0.476	0.850
Diamonds (sites)	0.272	4.058	0.327	5.496	0.227	2.293
Precious metals (sites)	100.5	1,135	213.2	1,686	8.456	36.90
Oil and gas (sites)	188.7	2,335	416.0	3,470	2.901	11.42
Observations	1.232		554		678	

Notes: Categorization into high-middle income and low-middle income subnations according to income with threshold at 3,466 USD average gross national income. Threshold follows the World Bank Analytical Classification in the year 2005.

Table B9: Definitions of variables and sources of data

Variable	Description
Corruption	Aggregated, score first within surveys and then across surveys, of all survey questions that fall within the category of corruption. Before aggregation responses with no upper bound are logged, all questions are made directionally consistent with higher values indicating higher level of corruption and all questions are standardized to a mean of zero and standard deviation of one. *Source:* Mitton (2016)
Log per capita income	Logarithm of average GDP per capita in the subnation. *Source:* various sources see Mitton (2016), additional data from (i) the Pakistan Bureau of Statistics for Pakistan collected in the PSLM survey 2016/2017 and (ii) the Nigeria Data Portal on Nigerian province statistics for the year 2006.
Log population	Logarithm of subnational population. *Source:* various sources see Mitton (2016).
Education	Average years of schooling from primary school onward for the population aged above 15. *Source:* Gennaioli, La Porta, Lopez-de Silanes & Shleifer (2012) and various sources taken from Eurostat for Denmark and Italy; MICS for Albania, Belarus, Kazakhstan, Kosovo, Montenegro, Nigeria, Uzbekistan; DHS program for Dominican Republic and Guatemala; Central Statistical Bureau of Latvia and constructed from neighbors for Rangpur (Bangladesh), Santa Cruz (Bolivia), Northern and Eastern Sri Lanka, Islamabad (Pakistan), Crimea (Ukraine), Vargas (Venezuela).
Seaports	Number of ports in subnation. *Source:* The World Port Index by the National Geospatial-Intelligence Agency. Authors' own calculation.
Airports	Number of airports in subnation. *Source:* Global Airport Database (Release 0.0.2-20170321). Authors' own calculation.
Capital city	Dummy, 1 if subnation constitutes or comprises the capital of the nation. *Source:* Google earth. Authors' own calculation.
Ethnic fractionalization	A set of 77 variables representing the percentage (by area) of each subnation that is home of a given ethnicity. *Source:* Weidmann, Rød & Cederman (2010).
Autonomous subnation	Dummy, 1 if subnation is autonomous or partly autonomous. *Source:* List of autonomous areas by country, Wikipedia https://en.wikipedia.org/wiki/List_of_autonomous_areas_by_country.
Border	Dummy, 1 if subnation is located at national border. *Source:* authors' own calculation.
Log land area	Logarithm of the size of subnation in square kilometer. *Source:* Google earth.
Terrain ruggedness	Average terrain ruggedness (in hundreds of meters) across all 30 by 30 arc-second cell contained within the subnation. *Source:* Nunn & Puga (2012).
Log stormrisk	Logarithm of the number of occurrences of hurricanes and tropical storms in the subnation between 1842 and 2010. *Source:* National Oceanic and Atmospheric Administration.
Log earthquakerisk	Logarithm on number of fault lines present in the subnation. *Source:* U.S. Geological Survey's Earthquake Hazards Program Data from Esri Disaster Response.
Precious metals	The number of identifiable mineral sites containing precious metals (gold, silver, or the platinum group) within the subnation, enters regression analysis scaled by 1,000 sites. *Source:* Mineral Resources Data System of the United States Geological Survey.
Diamonds	The number of identifiable mineral sites containing diamonds within the subnation, enters regression analysis scaled by 1,000 sites. *Source:* Mineral Resources Data System of the United States Geological Survey.
Oil and gas (sites)	The number of identifiable oil and/or natural gas sites within the subnation, enters regression analysis scaled by 1,000 sites. *Source:* United States Geological Survey and Petroconsultants International Data corporation (transformed from NAD 1927 to WGS 84 6).

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