Corruption: a cause or an effect?

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Abstract

The author's previous research (Littvay and Donica 2005) has identified significant correlates of corruption such as democratic and economic performance, ethnic tensions, aid and foreign direct investment. All of these studies assumed a causal direction, but none of them tested causality empirically. The purpose of this paper is to fill this hole by verifying that the theorized causal direction is empirically valid. Causal models utilize repeated measures data and structural equations modeling to infer causal direction. The analysis includes 186 countries from 1984 to 2002.

Introduction

This paper is part of a series of studies exploring the political and economic properties of corruption (Avery et al 2005, Donica and Littvay 2005, Littvay and Donica 2005). The authors' pervious work has longitudinally replicated Daniel Treisman's cross-sectional study on the causes of corruption (2000) and found that ethnic tension and democratic performance have the strongest impact on corruption. Treisman found fuels and minerals to be a strong predictor of corruption; our study suggested that fuels and minerals will have to be separated as only fuel export has a significant impact. Finally, Treisman found that GDP has a strong impact on levels of corruption.

Our study strives to gain more insight into how these significant political and economic indicators influence, and are influenced by levels of corruption. We utilize a granger causal path model to determine the causal direction between the indicators of interest. The study also includes government stability in addition to the indicators cited above, as preliminary research suggested that stability is strongly related to corruption. This paper is a direct continuation of the cited research agenda.

Review of Literature

Corruption in recent decades has been the topic of many studies (Mauro 1995, Treisman 2000, Knack 2001, Warren 2004). Early studies of corruption focused on a cost benefit analysis between corruption and the economic performance. Nye suggests that corruption will increase economic performance (1967). More recent studies have used statistical analysis to better understand the effect of perceived corruption on investment (Mauro 1995), democracy (Avery, et al 2005) and good governance (Knack 2001). These papers, implicitly or explicitly, assume a causal direction as they analyze corruption's correlates; none of them test the causal direction. This is the gap our study strives to bridge.

In order to illustrate corruptions theoretical causal direction with democratic performance, economic development, fuel and mineral endowments, ethnic conflict, and stability we use Norway and Nigeria as examples. Norway and Nigeria represent countries with different economic standings, but they do have two things in common. Norway and Nigeria both begin with the letter N and they both have large fuel and mineral deposits. However, Norway and Nigeria have both suffered different fates largely due to corruption. In the last 20 years Nigeria has fallen from one of the most democratic states in Africa to one of the most despotic, while Norway has stayed relatively stable (See table 1).

Table 1

Country	Democratic Performance[1]	% fuel and mineral exports as % of total exports[2]	Corruption Score[3]
Nigeria	(5,4)	97.9	1.674603
Norway	(1,1)	69.4	5.875

Norway and Nigeria are very different economically. Norway has a diversified economy that puts it at the top of world economies while Nigeria uses only its oil industry to promote economic growth. Mauro illustrated corruption hinders economic growth by creating a system of rents that investors have to pay to gain contracts (1995), further contracts are usually given out to elites or family members (Treisman 2000). These rents create oligarchs, destroy competition, and lower profits.

The democratic performance of Norway and Nigeria are also very different. Norway has a free and open society that exists as a check on the Norwegian Government. Treisman (2000) makes the point that democratic societies act as a natural check on corruption because civil society will seek out and ostracize corrupt government officials. Journalists will find corruption to expose it. Further, economically advanced democratic societies will likely come together to either try the corrupt official through impeachment, criminal proceeding, or elect someone new in their place. However, Nigeria has no such

[1] Score is the average from 1980-2003 Freedom House Report. (Scale 1-7, the two numbers are scores of Political Freedoms and Civil Liberties)
[2] Taken from WTO international trade statistics country profiles
[3] Score is the average of the perceived corruption score provided by PRS between 1984-2004 (Scale 1-6)

checks. The only check on Nigerian corruption comes from ethnic groups and groups that exist outside civil society such as insurgents[4]. Further the Nigerian government feels little pressure from its own citizens to push for democratic reforms. In much of Africa and the Middle East petrol dollars has undermined the traditional tax structures that helped democracies to develop in Europe (Tilly 1995; Karl 1997; Moore 1998).

Fuel and Mineral endowments have had a different impact on Norway and Nigeria. Norway and other Nordic countries have benefited from having fuel and mineral deposits, but Nigeria, other African countries, the Middle East, and South America have experienced a decline in their economic productivity and an increase in corruption (Dell 2004). Conversely, countries in East Asia with little mineral and fuel deposits have gone through economic booms and democratic tidal waves. The increased corruption in petro-countries can be attributed to the lack of over sight on the bureaucracy and executive branch caused by their reliance on mineral and fuel endowment for their economy (Treisman 2000).

Norway and Nigeria also differ in their participation in the International Monetary Fund and the World Bank (IMF/WB). Norway is a donor, while Nigeria is a recipient of assistance from both the IMF/WB. Through a quick overview of IMF/WB policies, it becomes clear these organizations operate on strong assumptions about the causal direction between the cited indicators and corruption. While the relationships between the variables have been confirmed by studies such as Treisman's (2000) we, to date, found no analysis of the causal direction between indicators of interest and corruption. It is our view, assumptions of causal direction need to be tested. We make no theoretical

[4] If it bleeds it leads. When things blow up that usually makes the news.

claim that the IMF/WB assumptions are reasonable or not. But we will use it as the foundation for our research hypothesis.

The IMF/WB prescribes unconditional combat of corruption since it is an inhibitor of growth (Mauro 2004). It also prescribes market liberalization, democratic reform and political economic stabilization even at costs of societies' social goals. While social goals to the IMF/WB policies are secondary, political stability is not.

However, reporting agencies have been of accused of misreporting corruption scores to show that the IMF/WB policies are working (Hanlon 2004). The prototypical example of misreported success stories is Malawi. Hanlon uses Malawi as an example of aid donors supporting corrupt elites when the elites promise to initiate market friendly reforms (2004). This increases corruption while a country democratizes. Donors do not want to criticize Malawi for being to corrupt, hence the under representation of corruption.

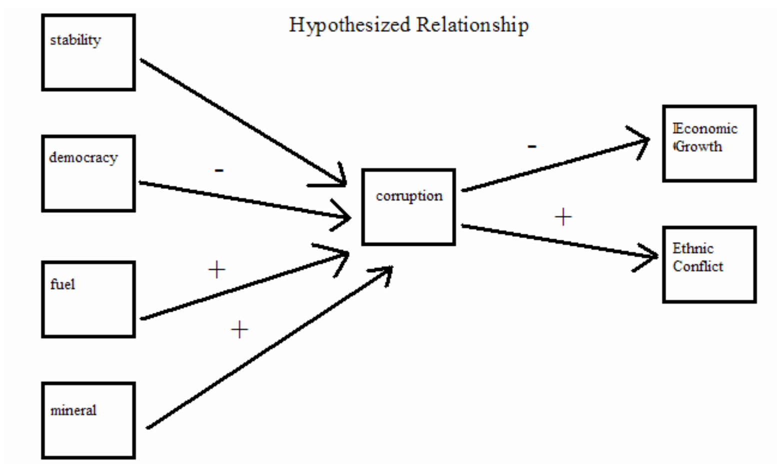
Loans and handouts are often conditioned on stable political institutions that are representative of all ethnic groups. Minimization of ethnic tension is clearly a must for a healthy economic society. From a theoretical perspective Warren argued that corruption is inherently undemocratic since it only allows few privileged to gain access to resources (2004). In ethnically tense situations, especially where political power is concentrated in the hands of one ethnic group, corruption can be seen as an unfair means for one ethnic group to gain resources and an advantage over the other ethnic group or groups[5]. This further elevates the tension.

[5] As it is seen in Nigeria.

Hypothesis

From the review cited above we expect that corruption will inhibit economic growth and will increase ethnic tension. We also expect that better government stability and democratic performance will dim corruption. Finally it is reasonable to expect that fuel and mineral resources will cause corruption to increase (the opposite expectation, that corruption will produce more fuel and mineral resources, is nonsensical.) See Figure 1 for illustration.

Figure 1



Operationalization of the Model

Our study is a quantitative test of the causal direction between the concepts of interest. This section explains how each of the variables was measured. To measure democratic performance we used Freedom House rankings. Freedom House measures democratic performance using a two dimension ordinal scale: “Political Rights” and “Civil Liberties.” Each country is ranked from 1 “most free” to 7 “not free.” For the purposes of this paper we combined the two scores to create one; -12, least democratic, thru 0, most democratic. Therefore a country like the United States would have a 0, while the wonderful vacation spots, North Korea and Mynamar (Burma) would have a -12.

Ethnic tension is measured using a six point scale compiled by the Political Risk Service (PRS). The countries with high ethnic tension are given lower rankings. This value was squared to reduce the skewed distribution of the observations and then flipped (high scores became low scores and vice versa) for easier interpretation. We use this variable in contrast to Treisman's use of Ethno linguistic fractionalization because it provides information for more countries over a wider range of time (2000).

Stability is also a PRS variable measured on a 12 point scale and defined as a government's ability to stay in power and carry out its proposed programs. It is a composite score of government utility, legislative strength and popular support. High numbers mean high government stability.

The corruption measure is also compiled by PRS. The scale is a 6 point scale measuring corruption within the political system: 6 being least corrupt and 1 being most corrupt. PRS's corruption index measures "…actual or potential corruption in the form of excessive patronage, nepotism, job reservations, 'favor-for-favors', secret party funding, and suspiciously close ties between politics and business" (PRS 2004). This variable was rescaled (high numbers to low numbers and vice versa) to improve interpretability. Transparency International data used by Treisman (2000) and others was considered initially as a measure of corruption, but as it is only available after 1995. Therefore, PRS corruption scores were purchased.[6]

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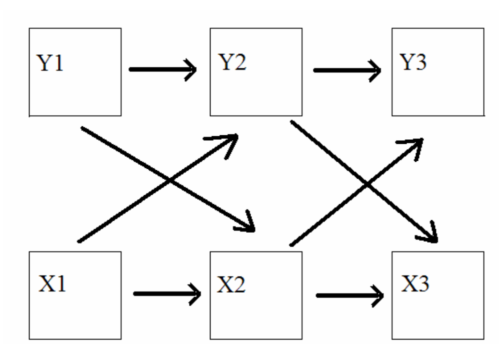
[6] The authors are grateful for the generous support of the University of Nebraska-Lincoln, Department of Political Science in financing the purchase of the dataset.

The economic variables: per capita GDP, fuel and mineral exports, were collected from the World Development Index. Fuel and mineral exports were used separately to proxy for natural resource endowments. Per capita GDP was used to measure economic performance and logged to normalize the variable distribution.

Methods

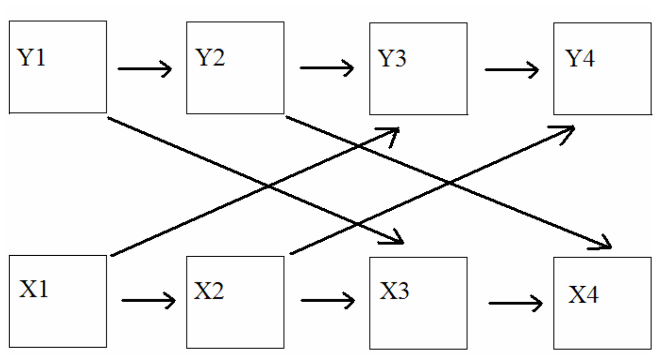
The analysis utilized granger causal path models as described in Finkel (1995). Path models allow for simultaneous estimation of two variables' impact on each other if the observed variable is measured at several time points. Basically it is the simultaneous estimation of X's impact at time 1 on Y at time 2 (after controlling for Y's own impact at the time 1) and Y's impact at time 1 on X at time 2, etc. The relationships are highlighted with a traditional regression coefficient and corresponding fit statistics. One significant relationship suggests causal direction. Two significant relationships suggest both variables affect each other. (See Figure 2.)

Figure 2



There are several problems with this analytical procedure. First, it assumes that the causal impact is actualized within the time that elapses between the two times of measurements. Since we have no theoretical expectations on how long it takes from variable X to have an impact on variable Y, multiple time lag structures were analyzed. This is possible since the amount of available data includes 19 annual readings starting in 1984. 10 different lag structures will be tested: immediate impact, 1 year, 2 year … 9 year lags. This allows for the detection of causation that only shows its effects after several years. For an illustration of the 2 year lag model see Figure 3.

Figure 3

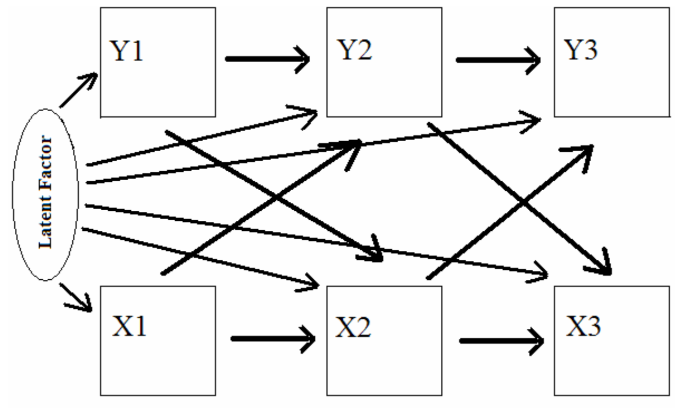


Another limitation of this model is the assumption of no spurious correlations between variables. The traditional way of controlling for this is striving for full specification of the model that includes all predictors. For cross-lag models this approach is problematic as any time varying predictors would exponentially increase the number of estimated parameters. Especially since path modeling requires specification of all possible relationships between variables, not just the relationship between the dependent and independent variables. To do this we would have a model that has substantially more estimated parameters than cases studied. While this is theoretically not problematic as path analysis uses the number of unique information in the covariance matrix, and not the number of cases for degrees of freedom. On the other hand the maximum likelihood estimator used here needs the large number of cases to be able to estimate the model. We are already in violation of sample size rules of thumb by only having 186 cases. This does not mean the models will have biased estimates; it only means the iterative process used to estimate the model have a higher probability of never ending (converging) or ending at nonsensical estimates (also called local solutions). In preliminary analyses we attempted to control for common independent variables, but it quickly became apparent that a different control will be necessary. (Similarly simultaneous estimation of different lag structures was also attempted without success.)

Controlling for possible predictors was solved by recommendations of Finkel to include a latent factor to extract common variance attributed to any possible common underlying causal source. (See Figure 4) This approach nullifies the autocorrelation between the studied time series data reducing the inflated fit parameters, also minimizing the effects of spurious correlations. Using a latent factor to extract common variance has its limitations as it assumed that the common source of correlation is non-time varying, but it greatly reduces the possibility of spurious correlation bias.

Many of our models had difficulty converging, or when they did, suspicion of a local solution was not ruled out. These results will not be reported leaving gaps in the model results tables. For completeness, the simple (no latent factor) model results are also reported. Note that the more significant relationships are probably inflated due to spurious and autocorrelations.

Figure 4



Path modeling of time series data suffers from a problem called empirical underidentification. The problem occurs when the correlation between two variables of the model is -1, 0, 1 or a number very close to -1, 0 and 1. These values are not useful unique information in the covariance matrix sucking up a degree of freedom decreasing the number of possible estimated parameters. Due to the autoregressive nature of time series data correlation between back to back readings on any variables are often 1 or very close to 1. To overcome this problem the estimated causal paths were equated across time. For example X1's impact on Y2 was equated to X2's impact on Y3 and etc., substantially decreasing the number of estimated parameters. This assumption is reasonable since the authors have no theoretical reason to believe that the relationship between X and Y would change substantially over time.

Missing data was treated with full information maximum likelihood estimation through the facilities built into the analytical software. This missing data treatment assumes data is "Missing at Random" (Little and Rubin 2002) which is generally a reasonable assumption with political economic data. In this case some bias might still emerge due to the lack of an extensive list of controls. All analyses were done in Mplus version 4 (Muthen and Muthen 2006).

Results

Detailed model results are presented in table 1 through table 6. They include the simplified model and latent factor model results. The coefficients and corresponding Z scores for the causal paths[7] and the list of path model fit statistics are reported[8]. Fit statistics can be used to determine which lag structure is the most realistic. Both models were estimated with regular (ML) and non-normality robust standard error maximum likelihood (MLR) estimation. Some fit statistics differ for the ML and MLR models. These should not be compared to each other, only across different lag structures.

A conceptual picture of the findings is in Figure 5. The main deviation from the hypothesis is in the direction of the relationship between corruption and ethnic tensions where ethnic tension appears to be the cause and corruption is the effect. Secondly, there is no significant relationship between mineral production and corruption. Finally, it is important to mention the relationship between GDP and corruption. 7 out of 10 of the more complex causal models did not converge. The no lag model (that did converge) verifies the hypothesis. The simpler model suggests possible non-recursive causation where economic decline can cause a delayed increase in corruption. The non-recursive relationship between GDP and corruption cannot be seen on the 9 year lag complex model. Since this reverse relationship (GDP causing Corruption) is not uniform for all

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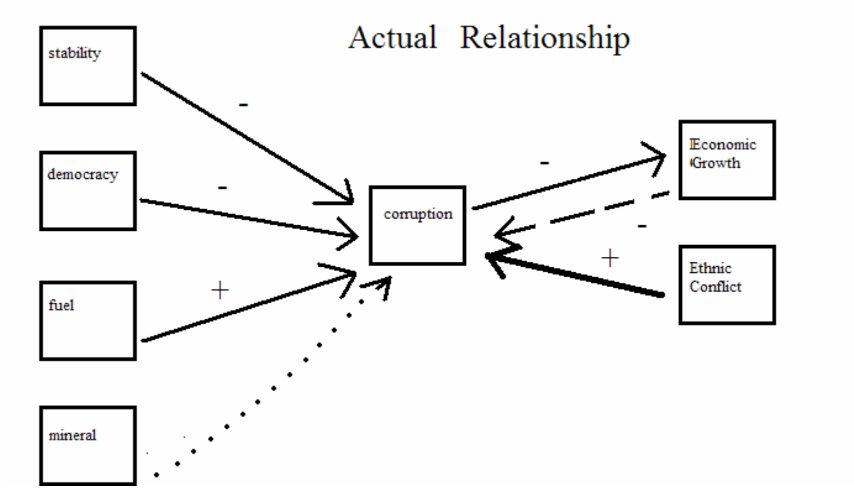
[7] So if the Z score is larger then the critical value of 1.96 (or smaller then -1.96) the coefficient is significant at .05 level. Critical value for .01 is 2.57, .10 is 1.65.

[8] Chi square tests are traditional tests of model fit for path models. For CFI and TLI strive for above .95 values, RMSEA below .08 and SRMR below .05 suggest good fit. AIC and BIC are tests of model comparison where lower number suggests better model. (Note AIC and BIC can be negative.)

lag structures, (only emerges after 4 year lags), we cannot rule out the possibility that it exists independent of spurious correlation. The models suggest support for all other elements of the hypotheses.

Figure 5



Discussion

The findings from these models partially support the IMF/WB hypothesis. It suggests that Treisman's model needs to be reworked. Finally, it confirms Warren's theory but warns about its expansions to ethnic divisions.

The IMF/WB's policies of pushing for liberalization, stability and open democratic processes might be well founded. The model does suggest that stability and democracy are the first steps in fighting corruption and are a precursor to growth. The less certain conclusion does warn the IMF in its considerations. It is possible that the prevention of decline or other means of encouraging growth is also key in fighting corruption. While these results are highly uncertain, they clearly call for more research on the long term effects of economic processes.

Author’s previous paper (Littvay and Donica 2005) found that minerals and fuels cannot be treated together as they have different impact on corruption. This study further verifies those findings as it shows that it also does not have extended temporal effects. This is where the Treisman’s model is in need of revisions.

And finally, while Warren claims corruption is inherently undemocratic, this claim suggests no direction. We deducted that if one group (possibly ethnic group) gains control of political power, that group’s activities could prevent the other groups from gaining rents. This can create tensions and therefore corruption can cause ethnic tensions. In light of the empirical evidence this reasoning is probably incorrect. It is ethnic tension that causes corrupt activities. This could be due to perceptions, as our corruption score is strictly a measure of perceived corruption. If there is ethnic tension, the ethnic group that gets fewer rents can perceive that as corrupt activity by the group in control. But it is also possible that ethnic tension does increase actual corruption as officials might feel that they can, or should, unjustly take from members of the other group for personal gain.

Our findings beg the question, what is the best way to combat corruption? Comparing Norway and Nigeria once again leads to the conclusion that an open and democratic society will help prevent corruption. Political stability helps. And any alleviation of ethnic tensions turned out to be a more important step then we initially hypothesized.

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Table 1: Causal Relationship between Corruption and Democratic Performance

simple model

	Chi-Sq (df=646)	Chi-Sq MLR	CFI	CFI MLR	TLI	TLI MLR	AIC	BIC	RMSEA	RMSEA MLR	SRMR	Y->Cor	z-score	z-score MLR	Cor->Y	z-score	z-score MLR
No Lag	1174.886	1205.322	0.967	0.956	0.964	0.952	10633.018	11062.042	0.066	0.068	0.086	-0.011	-5.636	-5.511	-0.016	-1.023	-1.164
1 year lag	1175.021	1205.727	0.967	0.955	0.964	0.952	10633.153	11062.177	0.066	0.068	0.086	-0.011	-5.611	-5.513	-0.015	-1.049	-1.187
2 year lag	1180.101	1212.246	0.967	0.955	0.964	0.951	10638.233	11067.257	0.067	0.069	0.089	-0.01	-4.99	-5.316	-0.024	-1.622	-1.939
3 year lag	1182.517	1216.64	0.967	0.955	0.964	0.951	10640.649	11069.674	0.067	0.069	0.088	-0.009	-4.233	-4.797	-0.042	-2.714	-3.081
4 year lag	1184.176	1219.754	0.967	0.954	0.964	0.95	10642.308	11071.332	0.067	0.069	0.089	-0.009	-3.956	-4.709	-0.046	-2.873	-3.157
5 year lag	1179.287	1215.487	0.967	0.955	0.964	0.951	10637.419	11066.443	0.067	0.069	0.084	-0.01	-4.141	-4.831	-0.058	-3.4	-3.487
6 year lag	1185.361	1221.578	0.966	0.954	0.964	0.95	10643.493	11072.517	0.067	0.069	0.098	-0.01	-4.003	-4.471	-0.044	-2.585	-2.813
7 year lag	1176.674	1210.822	0.967	0.955	0.964	0.951	10634.806	11063.83	0.066	0.069	0.096	-0.015	-5.275	-5.191	-0.031	-1.893	-2.107
8 year lag	1185.37	1220.396	0.966	0.954	0.964	0.95	10643.502	11072.526	0.067	0.069	0.113	-0.013	-4.445	-4.461	-0.028	-1.729	-1.889
9 year lag	1183.099	1218.049	0.967	0.954	0.964	0.951	10641.231	11070.255	0.067	0.069	0.117	-0.014	-4.626	-4.409	-0.031	-1.911	-2.019

complex model

	Chi-Sq (df=608)	Chi-Sq MLR	CFI	CFI MLR	TLI	TLI MLR	AIC	BIC	RMSEA	RMSEA MLR	SRMR	Y->Cor	z-score	z-score MLR	Cor->Y	z-score	z-score MLR
No Lag	1071.035	1123.585	0.971	0.959	0.967	0.953	10605.167	11156.77	0.064	0.068	0.044	-0.016	-5.106	-2.755	-0.015	-0.633	-0.525
1 year lag	1072.685	1132.082	0.971	0.958	0.967	0.952	10606.817	11158.42	0.064	0.068	0.046	-0.014	-4.97	-2.524	-0.012	-0.576	-0.442
2 year lag	1081.394	1276.481	0.971	0.947	0.966	0.939	10615.526	11167.129	0.065	0.077	0.063	-0.011	-4.51	-1.476	-0.028	-1.384	-0.707
3 year lag																	
4 year lag	1091.929	1181.474	0.97	0.954	0.965	0.947	10626.061	11177.664	0.065	0.071	0.039	0.004	0.769	0.284	0.037	1.022	0.306
5 year lag	1093.386	1146.71	0.97	0.957	0.965	0.951	10627.518	11179.121	0.066	0.069	0.042	0.001	0.157	0.139	-0.054	-2.031	-1.166
6 year lag	1092.642	1149.822	0.97	0.957	0.965	0.95	10626.774	11178.377	0.065	0.069	0.042	-0.001	-0.331	-0.286	0.01	0.389	0.219
7 year lag																	
8 year lag	1075.162	1127.404	0.971	0.959	0.966	0.952	10609.294	11160.897	0.064	0.068	0.039	-0.009	-2.42	-1.656	0.01	0.474	0.512
9 year lag	1087.245	1188.381	0.97	0.954	0.966	0.947	10621.377	11172.98	0.065	0.072	0.059	-0.014	-4.195	-2.411	-0.01	-0.421	-0.273

Table 2: Causal Relationship between Corruption and Stability

simple model

	Chi-Sq (df=646)	Chi-Sq MLR	CFI	CFI MLR	TLI	TLI MLR	AIC	BIC	RMSEA	RMSEA MLR	SRMR	Y->Cor	z-score	z-score MLR	Cor->Y	z-score	z-score MLR
No Lag																	
1 year lag	1058.791	1129.334	0.954	0.941	0.95	0.936	8556.519	8948.704	0.067	0.073	0.082	-0.016	-3.394	-3.412	-0.025	-1.596	-1.691
2 year lag	1062.112	1132.576	0.954	0.94	0.95	0.935	8559.841	8952.026	0.068	0.073	0.082	-0.01	-2.112	-2.015	-0.04	-2.597	-2.751
3 year lag	1059.378	1127.548	0.954	0.941	0.95	0.936	8557.107	8949.292	0.067	0.073	0.082	-0.011	-2.449	-2.374	-0.044	-2.848	-2.894
4 year lag	1067.862	1138.783	0.953	0.94	0.949	0.934	8565.59	8957.775	0.068	0.074	0.09	-0.007	-1.373	-1.339	-0.032	-2.018	-2.198
5 year lag	1070.506	1142.762	0.953	0.939	0.948	0.934	8568.234	8960.419	0.068	0.074	0.099	0	-0.046	-0.043	-0.029	-1.844	-1.977
6 year lag	1071.627	1144.087	0.952	0.939	0.948	0.934	8569.356	8961.541	0.068	0.074	0.101	-0.001	-0.221	-0.2	-0.024	-1.496	-1.682
7 year lag	1071.996	1143.945	0.952	0.939	0.948	0.934	8569.725	8961.91	0.068	0.074	0.102	-0.006	-1.004	-0.926	-0.015	-0.964	-1.111
8 year lag	1072.069	1145.532	0.952	0.939	0.948	0.934	8569.798	8961.983	0.068	0.074	0.109	0.003	0.557	0.487	-0.02	-1.224	-1.296
9 year lag	1071.237	1144.62	0.953	0.939	0.948	0.934	8568.966	8961.151	0.068	0.074	0.108	0.004	0.571	0.512	-0.025	-1.514	-1.52

complex model

	Chi-Sq (df=608)	Chi-Sq MLR	CFI	CFI MLR	TLI	TLI MLR	AIC	BIC	RMSEA	RMSEA MLR	SRMR	Y->Cor	z-score	z-score MLR	Cor->Y	z-score	z-score MLR
No Lag	934.203	1011.932	0.964	0.951	0.958	0.943	8507.931	9012.169	0.062	0.069	0.057	-0.015	-2.44	-2.182	0.021	0.808	0.701
1 year lag	935.848	1014.712	0.963	0.95	0.958	0.943	8509.576	9013.814	0.062	0.069	0.057	-0.01	-2.069	-1.763	0.017	0.715	0.629
2 year lag	940.216	1033.274	0.963	0.948	0.957	0.94	8513.945	9018.183	0.062	0.07	0.055	-0.005	-0.947	-0.555	0	0.003	0.003
3 year lag	938.792	1029.2	0.963	0.948	0.957	0.94	8512.521	9016.759	0.062	0.07	0.055	-0.009	-1.525	-1.084	-0.005	-0.206	-0.199
4 year lag	940.663	1031.968	0.963	0.948	0.957	0.94	8514.392	9018.63	0.062	0.07	0.054	0	0.047	0.041	-0.014	-0.65	-0.666
5 year lag	938.401	1027.287	0.963	0.949	0.957	0.941	8512.13	9016.368	0.062	0.07	0.054	0.009	1.355	1.16	-0.02	-0.866	-0.896
6 year lag	940.577	1022.533	0.963	0.949	0.957	0.941	8514.306	9018.544	0.062	0.07	0.06	-0.001	-0.241	-0.212	-0.005	-0.161	-0.149
7 year lag	940.75	1033.511	0.963	0.948	0.957	0.94	8514.478	9018.716	0.062	0.07	0.054	-0.004	-0.566	-0.501	-0.004	-0.152	-0.109
8 year lag	939.564	1034.327	0.963	0.948	0.957	0.94	8513.293	9017.531	0.062	0.071	0.055	0.009	1.161	0.911	-0.01	-0.372	-0.215
9 year lag	938.904	1034.829	0.963	0.948	0.957	0.94	8512.632	9016.87	0.062	0.071	0.057	0.01	1.275	1.086	-0.022	-0.816	-0.459

Table 3: Causal Relationship between Corruption and Ethnic Tensions
(Ethnic Tensions variable was squared to better aproximate normal distribution)

simple model

	Chi-Sq (df=646)	Chi-Sq MLR	CFI	CFI MLR	TLI	TLI MLR	AIC	BIC	RMSEA	RMSEA MLR	SRMR	Y->Cor	z-score	z-score MLR	Cor->Y	z-score	z-score MLR
No Lag																	
1 year lag																	
2 year lag	1112.134	1116.58	0.964	0.955	0.961	0.951	-4210.464	-3818.279	0.072	0.072	0.076	0.081	2.668	2.575	0.001	0.903	0.763
3 year lag	1116.883	1120.822	0.964	0.954	0.961	0.951	-4205.714	-3813.529	0.072	0.072	0.091	0.055	1.728	1.87	0.001	0.585	0.501
4 year lag	1115.871	1117.353	0.964	0.955	0.961	0.951	-4206.727	-3814.542	0.072	0.072	0.087	0.07	2.04	2.457	0.001	0.458	0.458
5 year lag	1115.542	1116.937	0.964	0.955	0.961	0.951	-4207.055	-3814.87	0.072	0.072	0.089	0.08	2.179	2.547	0	0.093	0.102
6 year lag	1115.488	1117.499	0.964	0.955	0.961	0.951	-4207.109	-3814.924	0.072	0.072	0.094	0.083	2.145	2.449	-0.001	-0.533	-0.583
7 year lag	1113.234	1115.404	0.964	0.955	0.961	0.951	-4209.364	-3817.179	0.072	0.072	0.088	0.108	2.633	2.7	0	-0.408	-0.428
8 year lag	1112.583	1115.185	0.964	0.955	0.961	0.951	-4210.014	-3817.829	0.072	0.072	0.095	0.111	2.581	2.75	-0.001	-1.034	-1.093
9 year lag	1109.806	1112.624	0.964	0.955	0.961	0.951	-4212.792	-3820.607	0.071	0.072	0.097	0.129	2.941	2.995	-0.002	-1.351	-1.487

complex model

	Chi-Sq (df=608)	Chi-Sq MLR	CFI	CFI MLR	TLI	TLI MLR	AIC	BIC	RMSEA	RMSEA MLR	SRMR	Y->Cor	z-score	z-score MLR	Cor->Y	z-score	z-score MLR
No Lag	1006.858	1121.877	0.969	0.951	0.965	0.943	-4239.739	-3735.501	0.068	0.077	0.07	0.087	2.684	2.454	0	0.223	0.167
1 year lag	1006.884	1121.389	0.969	0.951	0.965	0.943	-4239.714	-3735.476	0.068	0.077	0.069	0.084	2.681	2.415	0	0.179	0.136
2 year lag	1009.48	1124.777	0.969	0.95	0.964	0.943	-4237.117	-3732.879	0.068	0.078	0.078	0.071	2.191	2.152	0	-0.212	-0.158
3 year lag	1011.625	1127.729	0.969	0.95	0.964	0.942	-4234.972	-3730.734	0.069	0.078	0.09	0.052	1.576	1.523	0	-0.347	-0.289
4 year lag	1009.623	1126.023	0.969	0.95	0.964	0.943	-4236.975	-3732.737	0.068	0.078	0.079	0.073	2.107	2.072	0	0.224	0.203
5 year lag	1008.818	1123.167	0.969	0.951	0.964	0.943	-4237.779	-3733.541	0.068	0.078	0.078	0.085	2.299	2.064	0	0.177	0.172
6 year lag	1009.282	1126.395	0.969	0.95	0.964	0.943	-4237.316	-3733.078	0.068	0.078	0.082	0.085	2.201	2.118	0	-0.094	-0.083
7 year lag	1010.009	1034.763	0.969	0.959	0.964	0.953	-4236.589	-3732.351	0.068	0.071	0.052	0.128	2.745	2.092	-0.003	-1.768	-1.766
8 year lag	1008.477	1127.785	0.969	0.95	0.965	0.942	-4238.12	-3733.882	0.068	0.078	0.091	0.095	2.102	1.808	-0.001	-1.023	-0.935
9 year lag	1006.353	1128.505	0.969	0.95	0.965	0.942	-4240.244	-3736.006	0.068	0.078	0.094	0.11	2.353	1.9	-0.002	-1.396	-1.313

Table 4: Causal Relationship between Corruption and GDP
(GDP was logged to better aproximate normal distribution)

simple model

	Chi-Sq (df=646)	Chi-Sq MLR	CFI	CFI MLR	TLI	TLI MLR	AIC	BIC	RMSEA	RMSEA MLR	SRMR	Y->Cor	z-score	z-score MLR	Cor->Y	z-score	z-score MLR
No Lag																	
1 year lag																	
2 year lag	2190.269	2614.021	0.942	0.893	0.937	0.884	-4373.98	-3944.956	0.113	0.128	0.144	-0.01	-1.898	-1.571	-0.01	-7.428	-3.869
3 year lag	2197.301	2629.893	0.942	0.892	0.936	0.883	-4366.949	-3937.924	0.114	0.128	0.143	-0.01	-1.879	-1.608	-0.01	-6.821	-3.438
4 year lag	2201.654	2641.553	0.941	0.891	0.936	0.882	-4362.595	-3933.571	0.114	0.129	0.145	-0.014	-2.365	-1.931	-0.01	-6.37	-2.898
5 year lag	2200.282	2650.553	0.941	0.891	0.936	0.881	-4363.968	-3934.943	0.114	0.129	0.149	-0.018	-2.911	-2.399	-0.011	-7.038	-2.771
6 year lag	2199.284	2653.802	0.941	0.891	0.936	0.881	-4364.965	-3935.941	0.114	0.129	0.157	-0.025	-3.861	-3.092	-0.011	-6.801	-2.384
7 year lag	2194.136	2649.705	0.942	0.891	0.937	0.881	-4370.113	-3941.089	0.114	0.129	0.159	-0.03	-4.219	-3.284	-0.011	-7.258	-2.586
8 year lag	2187.772	2641.976	0.942	0.891	0.937	0.882	-4376.478	-3947.453	0.113	0.129	0.154	-0.029	-3.846	-3.269	-0.012	-8.393	-3.068
9 year lag	2192.125	2647.422	0.942	0.891	0.937	0.882	-4372.124	-3943.1	0.113	0.129	0.148	-0.027	-3.448	-2.968	-0.012	-7.982	-2.96

complex model

	Chi-Sq (df=608)	Chi-Sq MLR	CFI	CFI MLR	TLI	TLI MLR	AIC	BIC	RMSEA	RMSEA MLR	SRMR	Y->Cor	z-score	z-score MLR	Cor->Y	z-score	z-score MLR
No Lag	1726.772	2282.752	0.958	0.909	0.951	0.895	-4761.477	-4209.874	0.099	0.122	0.175	0.019	0.642	0.554	-0.004	-2.78	-2.146
1 year lag																	
2 year lag	1737.92	2284.753	0.957	0.909	0.951	0.895	-4750.33	-4198.727	0.1	0.122	0.177	0.02	0.706	0.695	-0.002	-0.933	-0.598
3 year lag																	
4 year lag																	
5 year lag																	
6 year lag																	
7 year lag																	
8 year lag																	
9 year lag	1608.826	1899.211	0.962	0.93	0.956	0.919	-4879.424	-4327.821	0.094	0.107	0.175	0.052	1.44	1.364	-0.001	-0.598	-0.276

Table 5: Causal Relationship between Corruption and Fuel Export

simple model

	Chi-Sq (df=646)	Chi-Sq MLR	CFI	CFI MLR	TLI	TLI MLR	AIC	BIC	RMSEA	RMSEA MLR	SRMR	Y->Cor	z-score	z-score MLR	Cor->Y	z-score	z-score MLR
No Lag	2106.768	2280.684	0.894	0.826	0.884	0.811	14962.425	15381.813	0.114	0.121	0.053	0.001	2.831	3.406	0.067	0.812	0.892
1 year lag	2106.544	2280.294	0.894	0.826	0.884	0.811	14962.202	15381.59	0.114	0.121	0.053	0.001	2.863	3.361	0.067	0.853	0.929
2 year lag	2107.725	2282.534	0.893	0.826	0.884	0.81	14963.383	15382.771	0.114	0.121	0.055	0.001	2.718	3.227	0.052	0.677	0.781
3 year lag	2109.365	2282.665	0.893	0.826	0.884	0.81	14965.023	15384.41	0.114	0.121	0.058	0.001	2.358	2.93	0.058	0.782	1.029
4 year lag	2109.783	2284.495	0.893	0.825	0.884	0.81	14965.441	15384.829	0.114	0.121	0.059	0.001	2.23	2.75	0.062	0.846	1.174
5 year lag	2110.693	2287.568	0.893	0.825	0.884	0.81	14966.35	15385.738	0.114	0.121	0.064	0.001	2.151	2.784	0.028	0.383	0.553
6 year lag	2108.324	2282.231	0.893	0.826	0.884	0.81	14963.982	15383.369	0.114	0.121	0.059	0.001	2.455	2.852	0.085	1.002	1.255
7 year lag	2109.765	2284.325	0.893	0.825	0.884	0.81	14965.423	15384.811	0.114	0.121	0.062	0.001	2.074	2.308	0.096	1.156	1.39
8 year lag	2111.021	2285.538	0.893	0.825	0.884	0.81	14966.679	15386.067	0.114	0.121	0.067	0.001	1.567	2.009	0.123	1.396	1.56
9 year lag	2111.866	2288.006	0.893	0.825	0.884	0.81	14967.524	15386.911	0.115	0.121	0.071	0	1.247	1.433	0.122	1.415	1.657

complex model

	Chi-Sq (df=608)	Chi-Sq MLR	CFI	CFI MLR	TLI	TLI MLR	AIC	BIC	RMSEA	RMSEA MLR	SRMR	Y->Cor	z-score	z-score MLR	Cor->Y	z-score	z-score MLR
No Lag	1643.455	2033.991	0.925	0.848	0.913	0.824	14575.112	15114.325	0.099	0.116	0.062	0.001	2.898	3.02	0.053	0.739	0.662
1 year lag	1643.297	2035.744	0.925	0.848	0.913	0.824	14574.955	15114.168	0.099	0.117	0.062	0.001	2.927	3.014	0.051	0.751	0.671
2 year lag	1643.954	2035.433	0.925	0.848	0.913	0.824	14575.612	15114.825	0.099	0.116	0.062	0.001	2.84	2.829	0.048	0.715	0.644
3 year lag	1645.999	2049.779	0.924	0.846	0.913	0.823	14577.657	15116.87	0.099	0.117	0.062	0.001	2.443	2.345	0.049	0.734	0.719
4 year lag	1647.003	2051.134	0.924	0.846	0.913	0.822	14578.661	15117.874	0.099	0.117	0.063	0.001	2.242	2.11	0.042	0.646	0.626
5 year lag	1648.014	2042.99	0.924	0.847	0.913	0.823	14579.672	15118.884	0.099	0.117	0.066	0.001	2.084	2.366	0.02	0.287	0.304
6 year lag	1645.391	2043.138	0.924	0.847	0.913	0.823	14577.048	15116.261	0.099	0.117	0.062	0.001	2.477	2.715	0.076	0.938	0.759
7 year lag	1646.585	2054.137	0.924	0.846	0.913	0.822	14578.242	15117.455	0.099	0.117	0.063	0.001	2.164	2.16	0.084	1.059	0.805
8 year lag	1648.066	2039.34	0.924	0.847	0.913	0.824	14579.723	15118.936	0.099	0.117	0.065	0.001	1.638	1.975	0.11	1.268	0.813
9 year lag	1649.042	2038.212	0.924	0.848	0.912	0.824	14580.699	15119.912	0.099	0.117	0.069	0	1.272	1.275	0.108	1.305	1.083

Table 6: Causal Relationship between Corruption and Mineral Export

simple model

	Chi-Sq (df=646)	Chi-Sq MLR	CFI	CFI MLR	TLI	TLI MLR	AIC	BIC	RMSEA	RMSEA MLR	SRMR	Y->Cor	z-score	z-score MLR	Cor->Y	z-score	z-score MLR
No Lag	2151.815	2520.561	0.891	0.824	0.882	0.808	12632.81	13052.964	0.116	0.129	0.058	0.001	1.399	1.481	-0.014	-0.385	-0.469
1 year lag	2151.741	2520.705	0.891	0.823	0.882	0.808	12632.736	13052.891	0.116	0.129	0.058	0.001	1.42	1.469	-0.014	-0.404	-0.486
2 year lag	2151.93	2520.684	0.891	0.823	0.882	0.808	12632.925	13053.08	0.116	0.129	0.058	0.001	1.349	1.335	-0.014	-0.405	-0.518
3 year lag	2152.239	2521.915	0.891	0.823	0.882	0.808	12633.234	13053.389	0.116	0.129	0.06	0.001	1.209	1.214	-0.017	-0.457	-0.504
4 year lag	2152.855	2524.953	0.891	0.823	0.882	0.808	12633.851	13054.005	0.116	0.129	0.062	0	0.999	0.916	-0.009	-0.24	-0.256
5 year lag	2152.368	2523.196	0.891	0.823	0.882	0.808	12633.363	13053.517	0.116	0.129	0.063	0.001	1.061	1.007	-0.026	-0.644	-0.665
6 year lag	2152.913	2523.999	0.891	0.823	0.882	0.808	12633.908	13054.063	0.116	0.129	0.068	0	0.637	0.551	-0.034	-0.768	-0.803
7 year lag	2152.422	2519.998	0.891	0.824	0.882	0.808	12633.418	13053.572	0.116	0.129	0.066	0	0.919	1.054	-0.037	-0.798	-0.836
8 year lag	2152.885	2519.901	0.891	0.824	0.882	0.808	12633.881	13054.035	0.116	0.129	0.071	0	0.423	0.463	-0.043	-0.916	-0.988
9 year lag	2151.996	2519.496	0.891	0.824	0.882	0.808	12632.992	13053.146	0.116	0.129	0.073	0	0.374	0.332	-0.064	-1.329	-1.421

complex model

	Chi-Sq (df=608)	Chi-Sq MLR	CFI	CFI MLR	TLI	TLI MLR	AIC	BIC	RMSEA	RMSEA MLR	SRMR	Y->Cor	z-score	z-score MLR	Cor->Y	z-score	z-score MLR
No Lag	1731.959	2056.2	0.919	0.864	0.906	0.842	12288.954	12829.152	0.103	0.117	0.047	0.002	1.927	1.557	-0.007	-0.219	-0.258
1 year lag	1732.849	2060.257	0.919	0.863	0.906	0.842	12289.844	12830.043	0.103	0.117	0.048	0.002	1.414	1.237	-0.007	-0.241	-0.281
2 year lag	1732.119	2057.192	0.919	0.864	0.906	0.842	12289.115	12829.313	0.103	0.117	0.048	0.002	1.796	1.481	-0.01	-0.334	-0.401
3 year lag	1732.914	2060.306	0.919	0.863	0.906	0.842	12289.91	12830.108	0.103	0.117	0.05	0.002	1.082	1.125	-0.016	-0.508	-0.541
4 year lag	1732.881	2062	0.919	0.863	0.906	0.842	12289.876	12830.075	0.103	0.117	0.049	0.002	0.994	1.22	-0.009	-0.297	-0.292
5 year lag	1732.027	2059.716	0.919	0.863	0.906	0.842	12289.022	12829.221	0.103	0.117	0.048	0.003	1.34	1.445	-0.019	-0.561	-0.476
6 year lag	1733.371	2067.308	0.919	0.863	0.906	0.841	12290.367	12830.565	0.103	0.117	0.05	0.001	0.565	0.762	-0.025	-0.692	-0.551
7 year lag	1733.454	2064.919	0.919	0.863	0.906	0.842	12290.45	12830.648	0.103	0.117	0.05	0.001	0.625	0.683	-0.03	-0.73	-0.579
8 year lag	1733.331	2063.029	0.919	0.863	0.906	0.842	12290.326	12830.525	0.103	0.117	0.05	0.002	0.954	0.869	-0.026	-0.576	-0.463
9 year lag	1732.459	2059.104	0.919	0.863	0.906	0.842	12289.454	12829.653	0.103	0.117	0.051	0.001	0.72	0.566	-0.058	-1.282	-1.036