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Corruption and Economic Growth: New Empirical Evidence*

Abstract

The nexus between corruption and economic growth has been examined for a long time. Many empirical studies measured corruption by the reversed Transparency International's Perception of Corruption Index (CPI) and ignored that the CPI was not comparable over time. The CPI is comparable over time since the year 2012. We employ new data for 175 countries over the period 2012-2018 and re-examine the nexus between corruption and economic growth. The cumulative long-run effect of corruption on growth is that real per capita GDP decreased by around 17% when the reversed CPI increased by one standard deviation. The effect of corruption on economic growth is especially pronounced in autocracies and transmits to growth by decreasing FDI and increasing inflation.

JEL code: C23, H11, K40, O11
Keywords: Perceived corruption, economic growth, panel data

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1. Introduction

Two theories describe how corruption is expected to influence economic growth. The "grease the wheels" hypothesis holds that corruption increases economic growth because corruption circumvents inefficient regulations. When regulations on starting businesses are tight, bribing politicians and bureaucrats is likely to give rise to vibrant economic activity. The "sand the wheels" hypothesis maintains, by contrast, that corruption decreases economic growth because corruption prevents efficient production and innovation. The empirical evidence tends to suggest that corruption decreases economic growth, especially in countries with low investment rates and low-quality governance (e.g., Mauro 1995, Mo 2001, Aidt et al. 2008, Méon and Sekkat 2005, Hodge et al. 2011, Swaleheen 2011, d'Agostino et al. 2016a and 2016b, Huang 2016, Tsanana et al. 2016, Chang and Hao 2017, Cieślik and Goczek 2018a and 2018b – see Campos et al. 2010 and Ugur 2014 for surveys).

Since the 2000s, many empirical studies examining the determinants and the economic and political consequences of corruption in the public sector used Transparency International's Corruption Perception Index (CPI). Examples include Paldam (2002 and 2019), Aidt (2009), Goel and Nelson (2010), Lessmann and Markwardt (2010), Méon and Weill (2010), Bjørnskov (2012), Potrafke (2012a and 2019), Cooray and Schneider (2018), Debski et al. (2018), and Vadlamannati and Cooray (2016). The studies on corruption and economic growth by Méon and Sekkat (2005), Swaleheen (2011), d'Agostino et al. (2016a and 2016b), Huang (2016), Tsanana et al. (2016), and Cieślik and Goczek (2018a) also employed the CPI. Studies using the CPI in panel data models ignored that the CPI was not comparable across countries and over time before 2012. In particular, including fixed period effects in panel data models does not solve the incomparability problem because the CPI in individual years before the year 2012 included data for different components and time periods to measure perceived corruption across continents. We believe that measuring corruption in the public sector by the CPI is suitable.

However, one cannot conclude from previous studies that corruption decreases growth, because the earlier version of the CPI is not comparable across time. Another important issue that many previous studies ignored is that economic growth may also influence corruption, because increasing living standards and incomes are often accompanied by an increasing quality of political institutions (Lipset hypothesis). We use jack-knifed regional averages of corruption for each country-year observation as instrumental variables for national corruption. Empirical evidence shows that corruption in an individual country or region is positively correlated with corruption in neighboring countries or regions (e. g., Becker et al. 2009, Faber and Gerritse 2012, Jetter and Parmeter 2018, Borsky and Kalkschmied 2019). Spatial dependence is a vigorous instrumental variable for corruption.

We employ the new CPI for 175 countries over the period 2012-2018 to re-examine the nexus between corruption and economic growth. Our study relates to new empirical growth models, which use annual dynamics in log real per capita GDP to examine determinants of economic growth (see, e.g., Acemoglu et al. 2019).[1] The cumulative long-run effect of corruption on growth is that real per capita GDP decreased by around 17% when the reversed CPI increased by one standard deviation. The effect of corruption on economic growth is especially pronounced in autocracies and countries with low government effectiveness and rule of law. Corruption is also found to affect foreign direct investment and inflation, which suggest that those variables may be channels of transmission from corruption to growth.

2. Previous studies

Previous studies on the corruption-growth nexus used cross-sectional and panel data. Scholars regressed economic growth on three prominent corruption measures: the International Country

[1] Other studies which employ five-year of ten-year averages of economic growth include Barro (2003), Durlauf et al. (2005), Levine (2005), Halter et al. (2014), Berg et al. (2018), and many more.

Risk Guide (ICRG) index, the World Governance Indicators (WGI) and Transparency International's Corruption Perception Index (CPI). The CPI is often considered to be an especially suitable measure for corruption, because the ICRG index measures investment risk of corruption rather than corruption per se, and the WGI's "Control of Corruption" sub-component has been criticized for several methodological issues (Thomas 2009, Langbein and Knack 2010, Qu et al. 2019).[2] The previous studies report direct correlations between corruption and economic growth and effects conditional on, for example, quality of governance. Scholars also dealt with endogeneity concerns between corruption and economic growth and employed instrumental variables such as ethnic fractionalization for corruption (Aidt et al. 2008). Excellent reviews of the previous studies till the year 2010 are Campos et al. (2010) and Ugur (2014). The results suggest that corruption and growth are negatively correlated; the evidence is quite strong. The meta-analysis of Ugur (2014) also suggests, for example, that the effects are less pronounced when long-run instead of short-run economic growth and only low-income countries are considered. We therefore relate to new studies published in 2011 or later that are not included in the previous survey articles and that measure corruption via the CPI. Table 1 surveys these studies.

New panel data studies corroborate that corruption has direct negative effects on economic growth (Swaleheen 2011, d'Agostino et al. 2016a and 2016b, Cieślik and Goczek 2018a). What is more, scholars investigate the functional form of the relationship between corruption and economic growth, transmission channels and the extent to which the relationship between corruption and economic growth is influenced by third variables. An interesting issue examined is whether the relationship between corruption and economic growth is linear. Swaleheen (2011) shows that the reversed CPI is negatively and the squared reversed CPI is

[2] Most importantly, criticism is leveled against the incomparability of the WGI's "control of corruption" sub-index regarding time and space, as many of the included country ranking are based on very different sources of information. Moreover, Qu et al. (2019) show that some important assumptions of the Unobserved Components Model (UCM) that is used to construct the WGI are violated.

positively correlated with economic growth, indicating the relationship between corruption and economic growth may be non-linear. D'Agostino et al. (2016a) propose that corruption decreases economic growth by promoting military expenditure. Corruption has also been shown to decrease growth when investment rates are small (Cieślik and Goczek 2018a).

Scholars have also examined the corruption-growth nexus in individual continents and regions. In Africa, corruption was negatively correlated with economic growth (d'Agostino et al. 2016b). In Asia, corruption was hardly associated with economic growth. In South Korea, however, corruption and economic growth were positively correlated (Huang 2016). In Europe, corruption was negatively (positively) correlated with economic growth in established (new) EU member countries (Tsanana et al. 2016).

3. Data and descriptive statistics

3.1 Data and descriptive statistics on corruption and real per capita GDP

To measure perceived corruption in the public sector, we use the reversed Transparency International's Perception of Corruption Index (CPI) over the period 2012-2018 for 175 countries.[3] We use the year 2012 as starting point because Transparency International changed the methodology to make the CPI comparable over time. The reversed CPI assumes values between 0 (no corruption) and 100 (extreme corruption). To construct the CPI, Transparency International aggregates data from several sources to provide perceptions by business people and country experts about the level of corruption in the public sector (Transparency International 2019). Figure (1) shows the prevalence of corruption across countries. Corruption is particularly pronounced in Somalia, South Sudan, Syria, and North Korea (the reversed CPIs

[3] Gutmann et al. (2015) describe the extent to which perceived and experienced corruption differ. On measuring corruption in the private sector see Gutmann and Lucas (2018).

are 83, 80, 80, and 79 in the year 2018). By contrast, corruption is low in Denmark, New Zealand, Sweden, and Switzerland (the reversed CPIs are 5, 6, 8, and 8 in the year 2018).

We use data on real per capita GDP from IMF (2019).[4] Median income in 2018 was 11,998 USD, but the data shows a high disparity in per capita GDP across countries. High income countries include Qatar (114,908 USD real per capita GDP in 2018), Luxembourg (97,002 USD), Singapore (87,281 USD), and Norway (66,018 USD). Low income countries include the Central African Republic (632 USD real per capita GDP in 2018), Burundi (651 USD), and the Democratic Republic of the Congo (725 USD).

The unconditional correlation between corruption (reversed CPI) and real per capita GDP (log) is strongly negative; the coefficient of correlation is $r = -0.71$ (see Figure 2).

3.2 Incomparability of the CPI over time for pre-2012 observations

In 2012, Transparency International conducted a fundamental update of the methodology underlying the CPI. Before 2012, Transparency International aggregated information from several years to obtain a measure of perceived corruption. This approach gave rise to an index that was comparable across countries at a given point in time, but the pre-2012 CPI was *not* comparable over time. In the 2012 Methodological Note, Transparency International emphasizes: "*Following a rigorous review process, some important changes have been made to the methodology in 2012. The method we use to aggregate different data sources has been simplified and also now includes just one year's data from each data source. Crucially, this method will allow us to compare scores over time, which was not methodologically possible previously. Given the changes to the methodology, it must be emphasized that country scores of the CPI 2012 cannot be compared against those of 2011 or previous editions. Year to year comparisons will be possible from 2012 onwards*" (Transparency International, 2012, p.1).

[4] To use data for the period 2012-2018, our dataset includes the IMF's forecasts of real per capita GDP for the most recent year(s) of the sample.

Including fixed period effects in a panel data model does not solve the issue of the CPI's incomparability over time, because the bias in comparability is distributed heterogeneously across continents and countries. For example, the 2011 version of the CPI includes data from the African Development Bank Governance Ratings 2010 for Africa, and data from the Political and Economic Risk Consultancy Asian Intelligence 2011 for Asian countries. This data is mixed with a total of 17 sources from 13 organizations, gathered between December 2009 and September 2011 (Transparency International, 2011). For this reason, using longitudinal data that includes country-year observations of the CPI for periods before 2012 will produce biased results.

4. Empirical Analysis

4.1 Empirical Specification

We estimate a dynamic panel data model

$$y_{it} = \gamma C_{it} + \sum_{j=1}^{\phi} \lambda_j y_{it-\phi} + \eta_i + \zeta_t + \varepsilon_{it}, \tag{1}$$

where y_{it} is the log of real per capita GDP in country i at time t, C_{it} is the reversed CPI to measure corruption, η_i is a country fixed effect that accounts for heterogeneity in time-invariant factors across countries (e.g. institutions, geography, culture), ζ_t is a period fixed effect that absorbs period-specific shocks (e.g. natural disaster, war, crises), and ε_{it} is the idiosyncratic error that includes any other time-variant unobservable shocks to GDP. An important assumption of Equation (1) is that ε_{it} is serially uncorrelated and that corruption and past GDP is orthogonal to current and future shocks to GDP, i.e.

$$E\left(\varepsilon_{it} \middle| y_{it-1}, \dots, y_{it_0}, C_{it}, \dots, C_{it_0}, \eta_i, \zeta_t\right) = 0. \tag{2}$$

To fulfill the sequential exogeneity assumption and to account for GDP dynamics, we follow Acemoglu et al. (2019) and include ϕ lags of y_{it}. Our baseline model specifies $\phi = 4$, which is based on the recommendation of Hamilton (2018), who shows that using four lags of y_{it} removes unit roots in the time series in Equation (1). Given Equation (2) and stationarity, Equation (1) can be estimated using the conventional Within-Group estimator. Table 2 shows descriptive statistics of the variables we use in the empirical analysis. Data on GDP and control variables are available before the year 2012. Our model therefore includes data for the full period 2012-2018.

4.2 Baseline results

Table 3 shows the results of the baseline model. Column (1) reports the reduced effect of corruption on real per capita GDP ($\phi = 0$). The parameter estimate is -0.005, suggesting that an increase in corruption by one standard deviation (19.56 points) decreases real per capita GDP by 10% in the short-run. The effect is statistically significant at the 1% level. Column (2) introduces GDP dynamics in the empirical model ($\phi = 4$), which decreases the point estimate of the corruption variable. The marginal effect of a one-standard-deviation change of corruption on real per capita GDP in Column (2) is -4.1% in the short-run; this effect is also statistically significant at the 1% level. The cumulative long-run effect of corruption is

$$\frac{\hat{\gamma}}{1 - \sum_{j=1}^{\phi} \hat{\lambda}_j},$$

and amounts to -17% when the estimates of Column (2) are used. Using lagged instead of contemporaneous levels of the reversed CPI does not change the inferences (Columns 3 and 4).

The estimates in Columns (2) and (4) have an asymptotic bias of order $1/T$, which results from the violation of strict exogeneity in dynamic panel models (Nickell-bias). However, neglecting GDP dynamics is likely to violate the sequential exogeneity assumption. In Columns (5) and (6), we therefore re-estimate Equation (1) in first-differences. Differencing the model also provides an alternative method to account for potential unit roots in the time-series that would violate the stationarity assumption necessary for unbiased estimates. The results from first-difference estimations corroborate the outcomes based on levels. The effect of corruption is negative in the reduced model (Column 5) and in the model including GDP dynamics (Column 6), and is statistically significant on the 1% level in both cases.

The negative correlation between corruption and economic growth remains statistically significant if we control for other variables that are likely to be correlated with corruption and economic growth such as investment, election years, fertility rates, and democracy (see Table A1 in the appendix).[5] However, many of these (and other) variables are not available for the most recent years of our sample, which is why the number of observations is substantially reduced when we include these variables into the empirical model.

4.3 Robustness

The updated CPI is comparable over time and hence suitable for panel data studies. In any event, the negative correlation between corruption and growth may still be driven by the methodology employed by Transparency International to construct the CPI. We therefore re-estimate Table 3 using data from the International Country Risk Guide (ICRG) from the PRS group. The ICRG consolidates 22 variables into three subcategories of country risks (political risk, financial risk, economic risk). The political risk dimension includes 12 weighted variables that are based on expert assessments and includes a measure of corruption in the form of excessive patronage, nepotism, job reservations, and suspiciously close ties between politics and business. Disadvantages of the ICRG data are that the number of included countries is smaller (131 in our sample) compared with the CPI (175 in our sample) and that the ICRG ratings are constructed for investment purposes and hence measure the investment risk of

[5] For a survey on what determines growth, see Barro (2003) and Moral-Benito (2012). Investment and population growth are key predictors of growth in the standard growth model. Electoral cycles and the degree of democratization are likely to influence growth and corruption (e. g. Gründler and Krieger 2016 and 2018, Potrafke 2012b and 2019). Because of data restrictions, other growth determinants (e.g. human capital) cannot be included.

corruption rather than corruption per se. Figure 3 shows that the reversed CPI and the corruption sub-component of the ICRG are positively correlated, but the number of country-year observations included in the common sample ($N = 795$) is (much) smaller than the sample of the reversed CPI ($N = 1{,}229$) or the ICRG ($N = 2{,}376$).

To employ a sufficiently large sample of observations, we use the ICRG data for the 2000-2018 period. The results in Table 4 show that inferences do not change when we employ the ICRG in model specifications identical to those of our baseline regressions. Compared to the baseline model, the marginal effect of a one-standard-deviation change (1.19 points) on economic growth is somewhat smaller (-4.1% in the short-run). Inferences do also not change when we restrict the sample to observations for which CPI data is available. In this case, the sample includes 777 country-year observations; the marginal effect size is more comparable (-7.2% for the ICRG and -10.7% for the CPI in the short-run).

The effect of corruption on GDP growth may be nonlinear (Méndez and Sepúlveda 2006). Figure 4 assesses potential nonlinearities in the corruption-growth nexus, conducting non-parametric estimations based on kernel-weighted local polynomial smoothing. The results are shown for the CPI (left panel) and the ICRG (right panel). In both cases, the estimated relationship is negative and hardly indicates any nonlinearities. If anything, the slope of the estimated function is zero for (very) low levels of corruption, but becomes negative and quite constant once the observations are outside the bottom decile of corruption.

4.4 Endogeneity

A potential concern regarding the baseline model is that $E(C_{it}|\varepsilon_{it}) \neq 0$ because of (i) reverse causation and (ii) omitted confounding factors. We account for the possibility of endogeneity in the corruption-growth nexus using jack-knifed regional averages of corruption as instrumental variables for national corruption levels. This strategy is motivated by the regional concentration of corruption. Corruption in an individual country has been shown to be positively correlated with corruption in neighboring countries; there is spatial dependence between and within countries (e. g., Becker et al. 2009, Faber and Gerritse 2012, Jetter and Parmeter 2018, Borsky and Kalkschmied 2019). Corruption is expected to be positively correlated between neighboring countries for manifold reasons. First, firms often trade and enjoy business relations with firms in neighboring countries. Business customs such as corruption are communicated across countries. Second, migration across neighboring countries transmits sociocultural attitudes. Third, political exchange between neighboring countries is also likely to give rise to common exposure to corruption. For example, governments maintain joint borders, regulate international trade, and execute common laws as administered by the European Union. Clearly, interrelations between firms, migration of citizens, and political exchange coincide and reinforce each other. For a more detailed discussion on how corruption is likely to transmit across neighboring countries see Borsky and Kalkschmied (2019).

Figure (1) shows that there is a distinct regional pattern of corruption, i.e. a country's national corruption level resembles the corruption level of its neighboring countries. We exploit this pattern to construct jack-knifed regional averages of corruption for each country-year observation as instrumental variables for the national degree of corruption. These "sharp instruments" are used in growth regressions (Cherif et al. 2018). We divide each continent into four disjoint regions $r \in \mathfrak{R}$ and compute the instrumental variable via[6]

$$\tilde{C}_{it} = \frac{1}{N_{rt} - 1} \sum_{\{j \neq i | r' = r, r' \in \mathfrak{R}\}} C_{it}.$$

Figure (2) shows the relationship between national and regional levels of corruption. The correlation between the variables is high (67%), implying that $\tilde{C}_{it}$ is a strong instrument for C_{it}.

[6] The classifications of regions follow Gründler and Krieger (2016). This classification divides each continent into four homogenous regions. Other classifications (such as the classification of the World Bank) are too broad, including, for instance, European and Asian countries into one large region. It is, however, not conceivable that spatial corruption influences national levels over such long distances.

The IV estimations are reported in Table 5. The results show that the effect of corruption remains negative and statistically significant at the 1% level if we instrument corruption with jack-knifed regional averages (Column 1). The first-stage results and the Stock-Wright and the Cragg-Donald tests suggest that the instrument is strong. The exclusion restriction requires that conditional on lags of GDP and country and year fixed effects, the level of corruption in neighboring countries is uncorrelated with national GDP. This assumption may be violated if regional levels of corruption influence national GDP by other means than their correlation with national corruption. The models reported in Columns (2)-(7) of Table 5 control for many factors that potentially violate the exclusion restriction, including trade flows, economic and interpersonal globalization, migration, and transportation infrastructure.[7] In each case, the parameter estimate of corruption remains negative and statistically significant.

Table 6 provides further assessments of the plausibility of the IV results. Columns (1)-(2) report the results from system GMM estimations based on internal instruments to expunge the endogenous components in the data. The effect of corruption remains negative and statistically significant at the 5% and 1% level. Column (3) re-estimates our IV specification using Lewbel-type instruments (Lewbel 2012). The Lewbel approach exploits model heteroskedasticity to construct valid instrumental variables based on the available regressors. Inferences do not change when we estimate our IV model with Lewbel instruments.

Finally, Column (4) conducts a placebo test of our IV strategy. To rule out that the IV results are based on weak instrumentation or sheer coincidence, we assign each country-year observation a randomly selected regional corruption level $\tilde{C}_{it}$ out of the pool of available observations on regional corruption. If the effect of spatial corruption on growth works via its

[7] Trade flows are from World Bank (2019) and are calculated as exports and imports divided by GDP. Economic and interpersonal globalization is measured via the sub-components of the KOF Globalization Index from Gygli et al. (2019) and Dreher (2006), see Potrafke (2015) for a survey on studies using the KOF index. Net migration is from the World Population Prospects of UN (2017), which contains data on migration in 5-year intervals. We interpolate the data to obtain a sufficiently large sample of observations. Availability of transportation infrastructure is proxied with the International Union of Railway’s data on rail lines (see UIC 2019).

correlation with national corruption, there should be no effect if we randomly assign regional corruption levels to countries. The results reported in Column 4 do not suggest that corruption influences growth when we employ placebo tests of our IV strategy.

4.5 Effects conditioned on governance and political institutions

Méon and Sekkat (2005) describe that the effect of corruption on economic growth depends on the quality of governance. We therefore estimate

$$y_{it} = \gamma C_{it} + \sum_{j=1}^{\phi} \lambda_j y_{it-\phi} + \delta C_{it} \times D_{it} + \theta D_{it} + \eta_i + \zeta_t + \varepsilon_{it}, \tag{3}$$

where D_{it} is the quality of governance. We proxy D_{it} via three indicators, including government effectiveness and rule of law (taken from the Worldwide Governance Indicators (WGI) database of World Bank, 2018) and the level of democracy (taken from Gründler and Krieger 2016 and 2018). The WGI database aggregates the views of many enterprise, citizen and expert survey respondents in industrial and developing countries and uses data from over 30 individual sources produced by a number of think tanks, survey institutes, non-governmental institutions, international institutions, and private firms. To facilitate the interpretation of the empirical results, we rescale both indicators k via $\tilde{k} = k + |\min(k)|$ so that $\tilde{k} > 0$. The democracy indicator of Gründler and Krieger (2016 and 2018) uses machine learning algorithms to produce fine-grained classifications of democracy on a continuous scale. Machine learning aggregation reduces arbitrariness in the classification and produces less non-random measurement errors than other existing democracy indicators (Gründler and Krieger 2019).

Table 7 shows the results. The effect of corruption on growth is significantly negative in countries with a low quality of governance and political institutions, but this effect is mitigated by better democratic governance. The marginal effect of corruption on economic growth at individual levels of our indicators for governance and political institutions is shown in Figure 6. In particular, when disentangling the effects of corruption on growth by political and economic institutions, Méon and Weill (2010) distinguish between the "weak form" and the "strong form" grease the wheels hypothesis. Overall, our results corroborate the "weak form" grease the wheels hypothesis. Figure 6 shows that the effect of corruption on growth is negative in less democratic countries and becomes insignificant in countries with established political institutions. A similar pattern occurs regarding government effectiveness and the rule of law, but the marginal effect of corruption on growth tends to be positive and statistically significant at the 5% level for very high levels of the variables. The empirical distributions of the variables, however, suggest that the positive correlation between corruption and growth for high levels of government effectiveness and rule of law is triggered by very few countries.[8] Most importantly, the marginal effect of corruption on growth is negative and statistically significant at the 5% level for the mean level of each variable. Support for the "strong form" grease the wheels hypothesis would require a larger set of country-year observations that gives rise to a positive marginal effect of corruption on growth.

4.6 Transmission channels

We examine the mechanisms through which corruption is likely to influence economic growth. The effect of corruption on real per capita GDP has been shown to be especially pronounced in countries with low investment rates: risk-averse investors prefer to invest in countries that enjoy low corruption and hesitate to invest in countries where corruption is prevalent (e. g., Cieślik and Goczek 2018a, Zakharov 2019). By lowering foreign direct investments (FDI), corruption indirectly decreased GDP growth. Corruption may also increase inflation rates and influence government size and education (e. g. Lambsdorff 2006, d'Agostino et al. 2016a; Farzanegan

[8] In case of government effectiveness, the marginal effects do not turn out to be statistically significant at the 5% level at the 90th percentile of the empirical distribution. In case of rule of law, the effect is statistically significant at the 5% level at the 90th percentile of the empirical distribution, but the effect is triggered by very few advanced economies (including Australia, Singapore, the United Kingdom, the Netherlands, and Sweden).

and Witthuhn 2017, Aidt 2019). We measure government size by two indicators: tax revenues of the government (in % of GDP) and final government consumption (in % of GDP). Regarding education, we account for both investment in the education sector (via public spending on education in % of GDP) and educational outcomes (via the persistence to the last grade of the primary school in % of the cohort). Data on inflation, taxes, government consumption, and education comes from World Bank (2019).

We estimate the effect of corruption on the transmission channels using models of the form

$$m_{it} = \gamma C_{it} + \sum_{j=1}^{\phi} \psi_j m_{it-\phi} + \sum_{j=1}^{\phi} \lambda_j y_{it-\phi} + \theta \mathrm{Open}_{it} + \eta_i + \zeta_t + \varepsilon_{it},$$

where m_{it} denotes the transmission variable in country i at time t, and open_{it} is the degree of openness to account for a countries' trade relations that may affect stability and foreign direct investments. Table 8 reports the results of the regressions. The results suggest that corruption decreased FDI and increased the inflation rate. Both effects are statistically significant at least at the 10% level. The outcomes also show that corruption does not affect national investment rates. We also find no effect of corruption on government consumption, taxes, or education.

5. Conclusion

Theoretical predictions about how corruption influences economic growth are ambiguous. The "grease the wheels" hypothesis predicts that corruption increases and the "sand the wheels" hypothesis predicts that corruption decreases economic growth. Empirical evidence tends to suggest that corruption decreases economic growth. However, many previous empirical studies measured corruption by Transparency International's Perception of Corruption Index (CPI) and ignored that the CPI was not comparable over time. Including fixed period effects does not solve the issue of incomparability over time.

We present new empirical evidence based on data for 175 over the period 2012-2018 – a period for which the CPI is comparable across countries and over time. The results show that corruption is negatively associated with economic growth. Real per capita GDP decreased by around 17% in the long-run when the reversed CPI increased by one standard deviation. The effect is especially pronounced in autocracies and countries with low government effectiveness and rule of law, supporting the "weak form" of the "grease the wheels" hypothesis. Transmission channels through which absence of corruption promotes economic growth seem to be preventing FDI and increasing instability.

Related studies by Becker et al. (2009), Faber and Gerritse (2012), Jetter and Parmeter (2018), and Borsky and Kalkschmied (2019) have shown that corruption in an individual country or region is positively correlated with corruption in neighboring countries or regions. We therefore use jack-knifed regional averages of corruption for each country-year observation as instrumental variables for the national degree of corruption. Spatial dependence is a vigorous IV for corruption. The IV-results corroborate the negative correlation between corruption and economic growth.

When low corruption promotes economic growth – accelerated by good governance and transmitted by channels such as FDI – citizens and policymakers have tools at hand to influence economic growth: fighting corruption, improving governance and advocating democracy, and attracting foreign investors.

Future research should re-examine the determinants and consequences of corruption (for a new survey on corruption see Aidt 2019). Many previous studies that use longitudinal data are based on the CPI simply ignored that the pre-2012 CPI was not comparable over time. The incomparability of the CPI gives rise to the concern that the obtained results may be biased. Re-examining the determinants and consequences of corruption including correlates such as government size, economic freedom and shadow economies, may hence be a promising avenue for future research.

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Table 1: Previous studies (later than 2010) on the corruption-growth nexus. Corruption measured by the CPI.
"-" negative correlation, "+" positive correlation, "0" correlation lacks statistical significance

Study	Time period	Countries included	Effect of corruption
Cieślik and Goczek (2018a)	1995-2014	142	- (especially when investment rates were small)
d'Agostino et al. (2016a)	1996-2010	97	-
d'Agostino et al. (2016b)	1996-2010	48 Africa	-
Huang (2016)	1997-2013	13 Asian-Pacific	0 (+ in South Korea)
Tsanana et al. (2016)	1995-2012	27 Europe	- (Western Europe) + (Eastern Europe)
Swaleheen (2011)	1995-2007	118	- (non-linear)

Other new studies on the corruption-growth nexus that do not use the CPI are Hodge et al. (2011), Chang and Hao (2018) and Cieślik and Goczek (2018b).

Table 2: Descriptive Statistics and Data Sources. 2000-2018 period.

	(1) Observations	(2) Mean	(3) Std. Dev.	(3) Min	(4) Max	(5) Data Source
Log(GDPpc)	3,628	9.11	1.22	6.14	11.89	IMF (2019)
CPI (reversed)	1,229	50.06	19.56	1.00	85.00	Transparency International (2019)
ICRG (reversed)	2,376	4.36	1.20	1.00	7.00	PRS Group
Democracy	2,675	0.68	0.34	0.00	0.97	Gründler and Krieger (2016, 2018)
Openness	3,213	90.79	52.59	0.17	442.62	World Bank (2019)
Election year	1,445	0.27	0.44	0.00	1.00	Potrafke (2019) and own calculations
Investment	2,056	3.88	4.16	-4.89	39.62	World Bank (2018)
Fertility	2,648	3.08	1.60	1.08	7.68	World Bank (2018)
FDI	3,341	5.73	16.29	-58.32	451.72	World Bank (2019)
Globalization (Interpersonal)	3,172	58.84	20.25	8.65	95.07	Gygli et al. (2019) and Dreher (2006)
Globalization (Economic)	3,111	57.63	15.51	20.50	95.43	Gygli et al. (2019) and Dreher (2006)
Net Migration	744	-109.15	642275	-4157896	5206538	UN (2017)
Rails	1,394	10426.05	24518.15	58.00	198057	UIC (2019)
Inflation	2,537	16.73	485.26	-35.84	24411.03	World Bank (2019)
Gov. Consumption	2,297	15.58	5.33	0.95	47.19	World Bank (2019)
Tax Revenue	1,784	17.24	7.60	0.32	62.86	World Bank (2019)
Persistence to Last Grade	1,474	83.38	17.93	23.35	100.00	World Bank (2019)
Public Spending (Education)	3,311	4.66	3.89	-25.47	65.79	World Bank (2019)
Rule of Law	3,231	2.56	0.99	0.00	4.71	World Bank (2018)
Government Effectiveness	3,201	2.44	0.98	0.00	4.92	World Bank (2018)
N	3,707					

Notes: The table reports descriptive statistics of the variables used in the empirical analysis, including the number of observations, the mean, the standard deviation, the minimum and the maximum value. Data sources are listed in Column (5). Statistics refer to the complete time period 2000-2019. The number of observations in the individual regressions is (much) smaller in some cases because of the unavailability of the new CPI before 2011. Net migration is interpolated, as the data is only available in 5-year steps.

Table 3: Regression Results. Dependent variable: Log (real per capita GDP). Regression measured via the reversed CPI.

	Contemporaneous Corruption		**Lagged Corruption**		**Lagged Corruption**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Levels	Levels	Levels	Levels	Differences	Differences
Corruption	-0.005***	-0.002**				
	(0.002)	(0.001)				
Corruption $(t-1)$			-0.005***	-0.001**		
			(0.001)	(0.000)		
Δ Corruption $(t-1)$					-0.002***	-0.001***
					(0.001)	(0.000)
Log(GDP^{pc}) $(t-1)$		0.696***		0.909***		0.465***
		(0.135)		(0.074)		(0.082)
Log(GDP^{pc}) $(t-2)$		0.070		-0.221***		-0.150*
		(0.060)		(0.046)		(0.076)
Log(GDP^{pc}) $(t-3)$		0.058		-0.004		0.100***
		(0.061)		(0.031)		(0.011)
Log(GDP^{pc}) $(t-4)$		-0.049		-0.055		-0.000
		(0.050)		(0.061)		(0.071)
Observations	1,194	1,192	1,194	1,193	1,010	1,009
Countries	175	175	175	175	175	175
R-Squared	0.467	0.997	0.459	0.998	0.019	0.309
F Stat	13.10	181.8	28.24	152.7	2.969	28.21
F p-val	0.000	0.000	0.000	0.000	0.009	0.000

Notes: Cluster-robust standard errors reported in parentheses, each model includes fixed period effects.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Robustness Checks. Dependent variable: Log (real per capita GDP), corruption measured via the reversed ICRG. 2000-2018 period.

	Contemporaneous Corruption		**Lagged Corruption**		**Lagged Corruption**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Levels	Levels	Levels	Levels	Differences	Differences
Corruption	-0.035*	-0.011**				
	(0.019)	(0.0005)				
Corruption $(t-1)$			-0.041**	-0.009*		
			(0.019)	(0.005)		
Δ Corruption $(t-1)$					-0.012**	-0.010*
					(0.006)	(0.006)
Log(GDP^{pc}) $(t-1)$		0.884***		0.906***		0.0641
		(0.132)		(0.130)		(0.142)
Log(GDP^{pc}) $(t-2)$		0.056		-0.050		0.055
		(0.121)		(0.115)		(0.131)
Log(GDP^{pc}) $(t-3)$		0.053		0.045		0.038
		(0.044)		(0.042)		(0.043)
Log(GDP^{pc}) $(t-4)$		-0.125**		-0.125**		-0.161***
		(0.048)		(0.050)		(0.035)
Observations	2,342	1,822	2,342	1,951	2,211	1,820
Countries	131	131	131	131	131	131
R-Squared	0.448	0.869	0.438	0.885	0.065	0.123
F Stat	20.59	672.7	22.36	770.3	13.92	24.17
F p-val	0.000	0.000	0.000	0.000	0.009	0.000

Notes: Cluster-robust standard errors reported in parentheses, each model includes fixed period effects.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Accounting for Endogeneity. Instrumental variable: jack-knifed regional averages of corruption. Dependent variable: Log (real per capita GDP).

	REDUCED	GDP DYNAMICS	TRADE	GLOBALIZATION	MIGRATION	INFRASTUCTURE	ALL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Corruption	-0.034***	-0.008*	-0.032***	-0.026**	-0.029**	-0.037***	-0.038**
	(0.0131)	(0.005)	(0.012)	(0.012)	(0.013)	(0.012)	(0.015)
Log(GDP^{pc}) $(t-1)$		0.674***					
		(0.125)					
Log(GDP^{pc}) $(t-2)$		0.053					
		(0.060)					
Log(GDP^{pc}) $(t-3)$		0.068					
		(0.060)					
Log(GDP^{pc}) $(t-4)$		-0.045					
		(0.049)					
Trade			-0.000				0.000
			(0.001)				(0.001)
Globalization (Economic)				-0.000			-0.005
				(0.002)			(0.004)
Globalization (Interpersonal)				0.003			0.012
				(0.005)			(0.009)
Net Migration					0.000*		0.000**
					(0.000)		(0.000)
Rail Lines						0.000	0.000
						(0.000)	(0.000)
Observations	1,194	1,192	1,123	989	1,181	447	367
Countries	175	175	166	169	173	73	69
R-Squared	0.467	0.997	0.457	0.279	0.330	0.081	0.390
F Stat	6.260	122.2	7.71	5.52	7.59	5.47	4.95
F p-val	0.000	0.000	0.000	0.000	0.000	0.006	0.000
Cragg-Donald	15.478	11.782	17.275	8.892	13.655	41.859	19.679
Stock-Yogo (20% IV)	6.66	6.66	6.66	6.66	6.66	6.66	6.66
First-Stage	0.215**	0.188**	0.242**	0.169*	0.206**	0.586***	0.488***

Notes: Table reports IV regressions with jack-knifed regional levels of corruption used as instrumental variable. Cluster-robust standard errors reported in parentheses. Models include country fixed effects. Cragg-Donald reports the F statistic of the Cragg-Donald test, with corresponding Stock-Yogo critical values for a maximal 20% IV size. Net migration is interpolated because of restricted data availability.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Accounting for Endogeneity. Dependent variable: Log (real per capita GDP).

	System GMM		Further IV Tests	
	ONE LAG	FOUR LAGS	LEWBEL	PLACEBO
	(1)	(2)	(3)	(4)
Corruption	-0.005***	-0.004**	-0.004*	-0.048
	(0.002)	(0.002)	(0.002)	(0.068)
Log(GDP^pc) $(t-1)$	0.912***	1.059***	0.959***	0.449
	(0.028)	(0.90)	(0.120)	(0.281)
Log(GDP^pc) $(t-2)$		-0.106***	0.114	-0.593
		(0.036)	(0.087)	(0.201)
Log(GDP^pc) $(t-3)$		0.050	0.052	0.171
		(0.047)	(0.053)	(0.158)
Log(GDP^pc) $(t-4)$		-0.079*	-0.132	-0.029
		(0.045)	(0.025)	(0.085)
Openness			0.000	0.000
			(0.000)	(0.001)
Observations	1,194	1,192	1,123	1,123
Countries	175	175	173	173
R-Squared			0.241	-1.375
F Stat			11.54	15.67
F p-val			0.000	0.000
Cragg-Donald			55.22	0.568
Stock-Yogo (20% IV)			6.77	6.66
First-Stage				
Diff-Hansen	0.972	0.800	0.800	
AR(1) p-val	0.032	0.100	0.100	

Notes: Cluster-robust standard errors reported in parentheses, each model includes fixed period effects. Column (1)-(2) apply two-step system GMM regressions using a collapsed instrument matrix that includes all available lags (Windmeijer-corrected standard errors). The Columns labeled "further IV tests" feature two additional tests, using Lewbel instruments (see Lewbel, 2012) and a placebo regression that employs randomly assigned regional levels as instruments. Cragg-Donald reports the F statistic of the Cragg-Donald test, with corresponding Stock-Yogo critical values for a maximal 20% IV size. Diff-Hansen p-val reports the Hansen test for validity of the additional orthogonality conditions of system GMM, and AR(1) p-val tests for serial correlation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Conditional Effects. Dependent variable: Log (real per capita GDP).

	Government Effectiveness		Rule of Law		Democracy	
	(1)	(2)	(3)	(4)	(5)	(6)
Corruption	-0.015***	-0.007*	-0.016***	-0.008*	-0.021**	-0.010**
	(0.005)	(0.001)	(0.006)	(0.004)	(0.010)	(0.005)
Log(GDP^pc) $(t-1)$		0.570***		0.561***		0.448***
		(0.177)		(0.176)		(0.170)
Log(GDP^pc) $(t-2)$		0.083*		0.070		0.116
		(0.049)		(0.043)		(0.104)
Log(GDP^pc) $(t-3)$		0.082		0.075		0.235
		(0.087)		(0.085)		(0.155)
Log(GDP^pc) $(t-4)$		-0.007		-0.016		0.066
		(0.046)		(0.046)		(0.065)
Corruption × Gov. Effect.	0.005**	0.002*				
	(0.002)	(0.001)				
Corruption × Rule of Law			0.005**	0.003*		
			(0.002)	(0.001)		
Corruption × Democracy					0.021*	0.010*
					(0.012)	(0.005)
Government Effectiveness	0.005*	0.125*				
	(0.002)	(0.064)				
Rule of Law			0.425***	0.184**		
			(0.149)	(0.088)		
Democracy					0.779	0.407*
					(0.491)	(0.209)
Observations	1,001	999	1,001	999	839	837
Countries	172	172	172	172	173	173
R-Squared	0.412	0.996	0.405	0.991	0.232	0.993
F Stat	14.42	94.25	20.44	85.72	11.54	79.09
F p-val	0.000	0.000	0.000	0.000	0.000	0.000

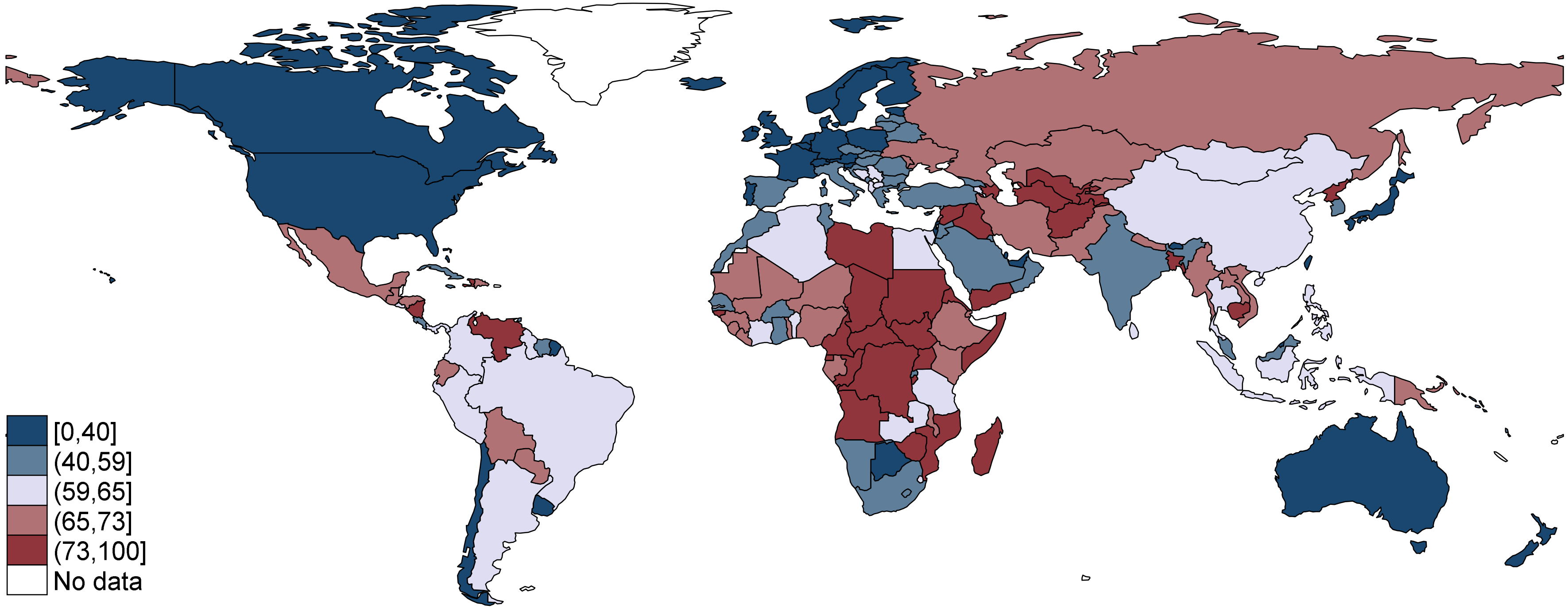
Notes: Table reports effects of corruption conditional on governance and the quality of political institutions. Cluster-robust standard errors reported in parentheses, each model includes fixed period effects. Data on government effectiveness and the rule of law is taken from the Worldwide Governance Indicators database from World Bank (2018). Data is rescaled so that the values are in the positive parameter space. Democracy is measured using the continuous indicator of Gründler and Krieger (2016, 2018). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Transmission Channels of Corruption to Economic Growth.

	INVESTMENT		INFLATION	GOVERNMENT SIZE		EDUCATION	
	National Investment	Foreign Direct Investment	Inflation Rate	Tax Revenues	Government Spending	Public Spending on Education	Persistence to last grade of primary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Corruption	0.014	-0.219*	0.236**	0.003	-0.030	0.143	0.246
	(0.052)	(0.115)	(0.105)	(0.033)	(0.021)	(0.218)	(0.191)
Log(GDP^{pc}) $(t-1)$	3.662	8.369	1.101	-1.986	-2.390	-1.863	-0.047
	(4.852)	(5.359)	(17.999)	(3.679)	(2.540)	(2.333)	(0.140)
Log(GDP^{pc}) $(t-2)$	-10.398*	-6.818	-37.248	8.312	-1.205	4.203*	-0.156
	(6.127)	(5.238)	(28.485)	(7.862)	(2.658)	(2.162)	(0.148)
Log(GDP^{pc}) $(t-3)$	5.817	-6.301	162.699**	3.124	-1.989	-2.921*	0.041
	(4.085)	(3.941)	(68.905)	(6.360)	(3.087)	(1.567)	(0.185)
Log(GDP^{pc}) $(t-4)$	-3.010	3.920	-145.948**	-11.667**	5.511*	0.870	-0.181
	(3.140)	(3.735)	(60.425)	(4.691)	(3.066)	(1.607)	(0.135)
$m\ (t-1)$	0.535***	0.003	0.605**	0.497***	0.486***	0.275***	-10.163
	(0.119)	(0.061)	(0.244)	(0.176)	(0.079)	(0.098)	(9.212)
$m\ (t-2)$	-0.184***	0.009	-0.109	-0.003	-0.017	-0.249*	22.847
	(0.069)	(0.051)	(0.101)	(0.120)	(0.056)	(0.147)	(18.973)
$m\ (t-3)$	-0.133**	-0.070	-0.325	-0.105	-0.090	0.004	-8.483
	(0.064)	(0.054)	(0.255)	(0.128)	(0.081)	(0.094)	(18.434)
$m\ (t-4)$	0.013	0.018	0.049	0.006	-0.210***	-0.214	16.063
	(0.049)	(0.103)	(0.119)	(0.064)	(0.059)	(0.154)	(10.532)
Openness	0.070	0.033	0.097**	-0.002	-0.013*	0.004	0.059
	(0.048)	(0.034)	(0.045)	(0.013)	(0.007)	(0.022)	(0.045)
Observations	744	761	751	437	759	287	170
Countries	164	160	160	113	160	92	57
R-Squared	0.145	0.182	0.056	0.390	0.572	0.235	0.534
F Stat	5.45	2.97	3.49	3.09	11.09	1.45	0.89
F p-val	0.000	0.000	0.000	0.000	0.000	0.149	0.572

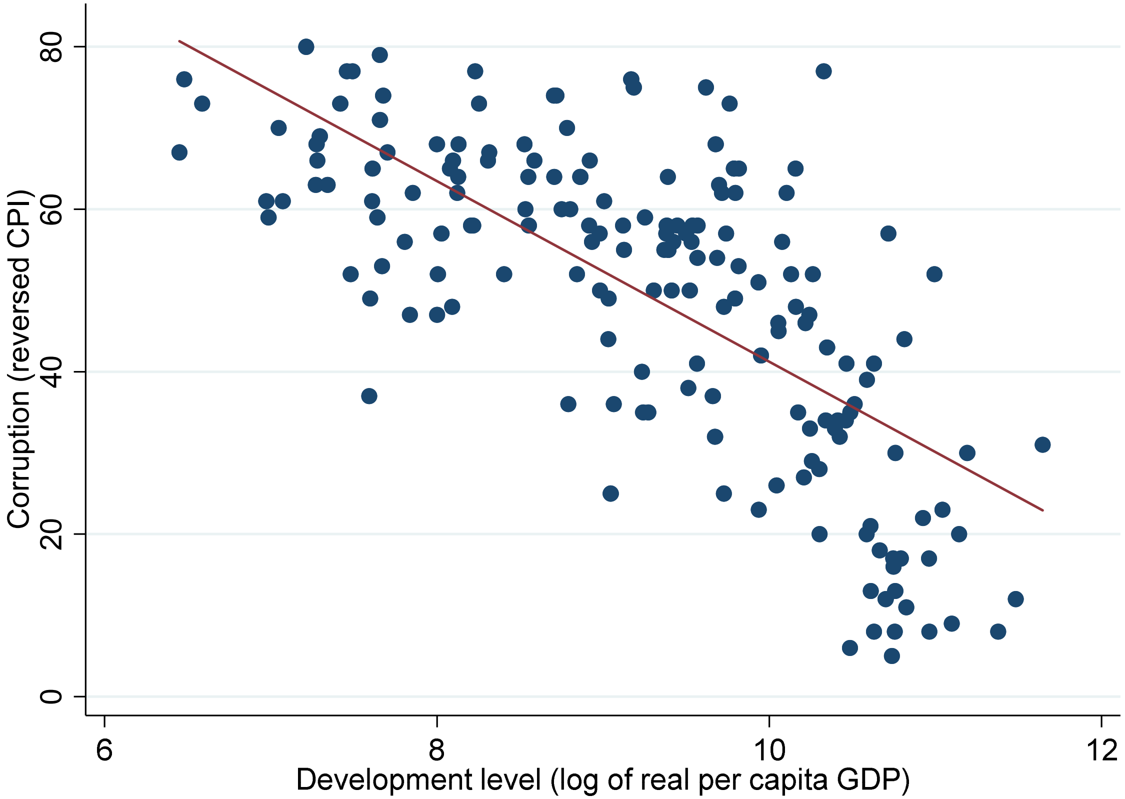
Notes: Table reports effects of corruption on transmission variables. Cluster-robust standard errors reported in parentheses, each model includes fixed country and period effects. Data on the transmission variables comes from the World Development Indicators database from World Bank (2019). Tax revenues, government spending, and public spending on education is coded as percentage of GDP, persistency to last grade of primary is the percentage of children enrolled in the first grade of primary school who eventually reach the last grade of primary education and is coded in % of the cohort. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Corruption in the World, 2018.



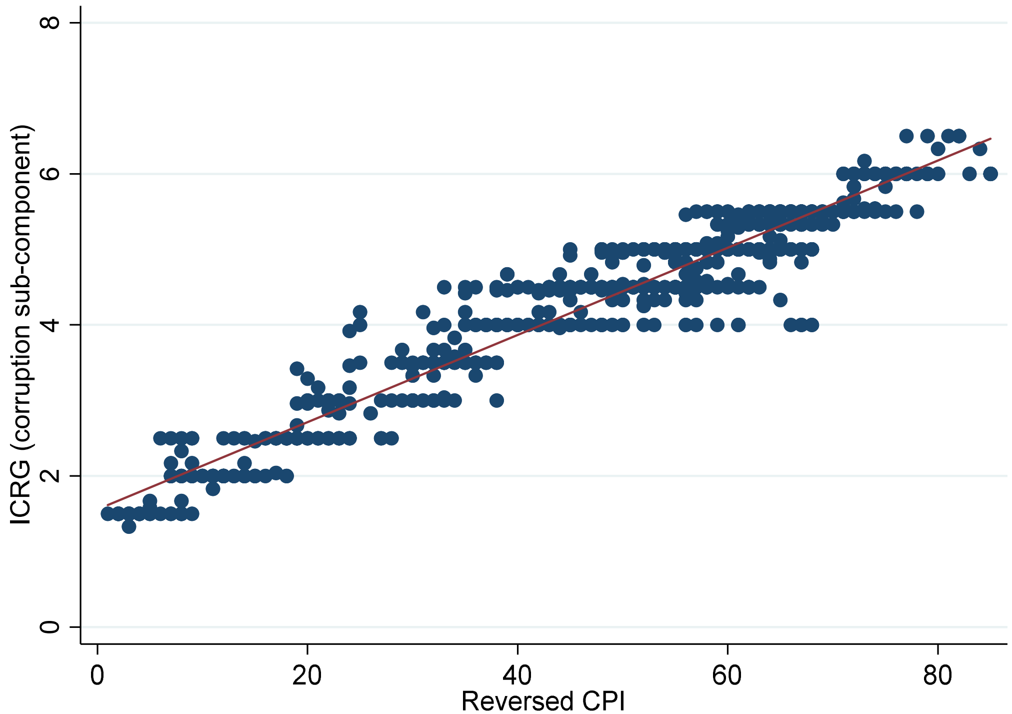
Notes: The figure shows the extent of corruption in the world, measured via the reversed CPI Index from Transparency International (2018). Low values (blue) reflect low extents of corruption, while high values (red) reflect high prevalence of corruption. The quintiles used in the figure are recovered from the empirical distribution of the CPI in 2018.

Figure 2: Corruption and Development Levels, 2018.



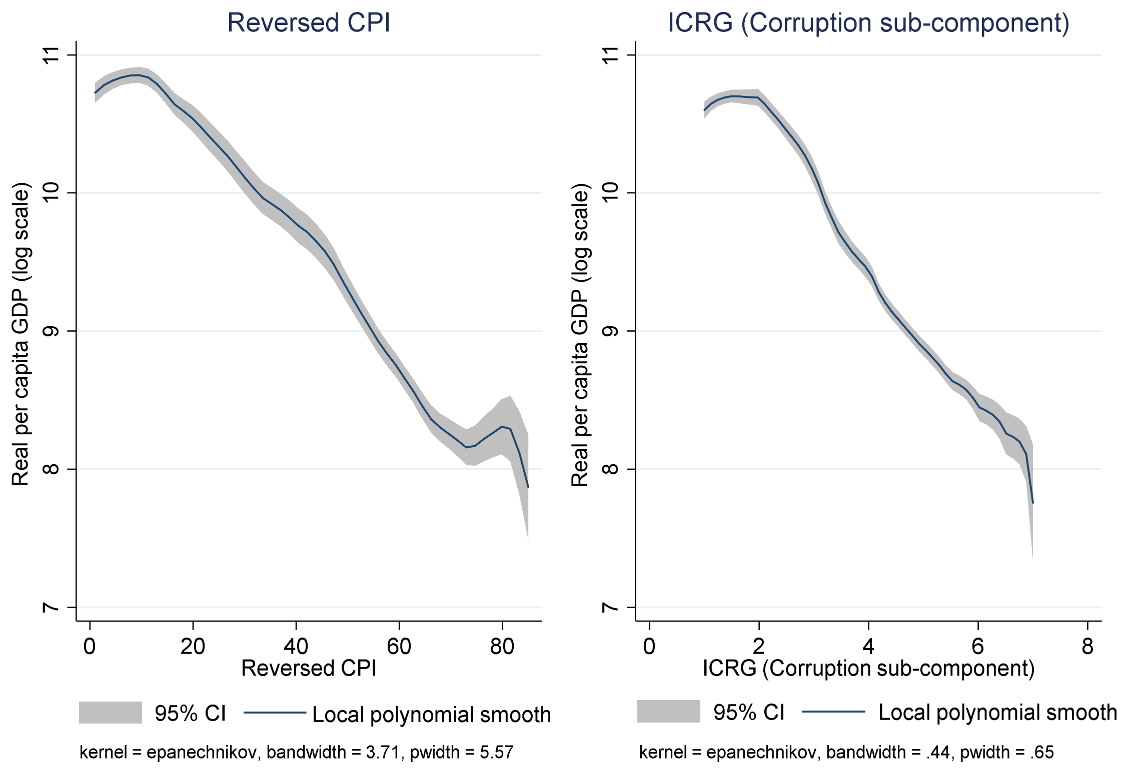
Notes: The figure shows the correlation between corruption (measured via the reversed CPI) and the development level (measured via the log of real per capita GDP) for the year 2018. The coefficient of correlation is 70.51%. Over the whole period for which comparable data is available (2012-2018), the coefficient of correlation is also 70.52%.

Figure 3: Comparison of Corruption Measures, Reversed CPI versus ICRG (Corruption Sub-Component).



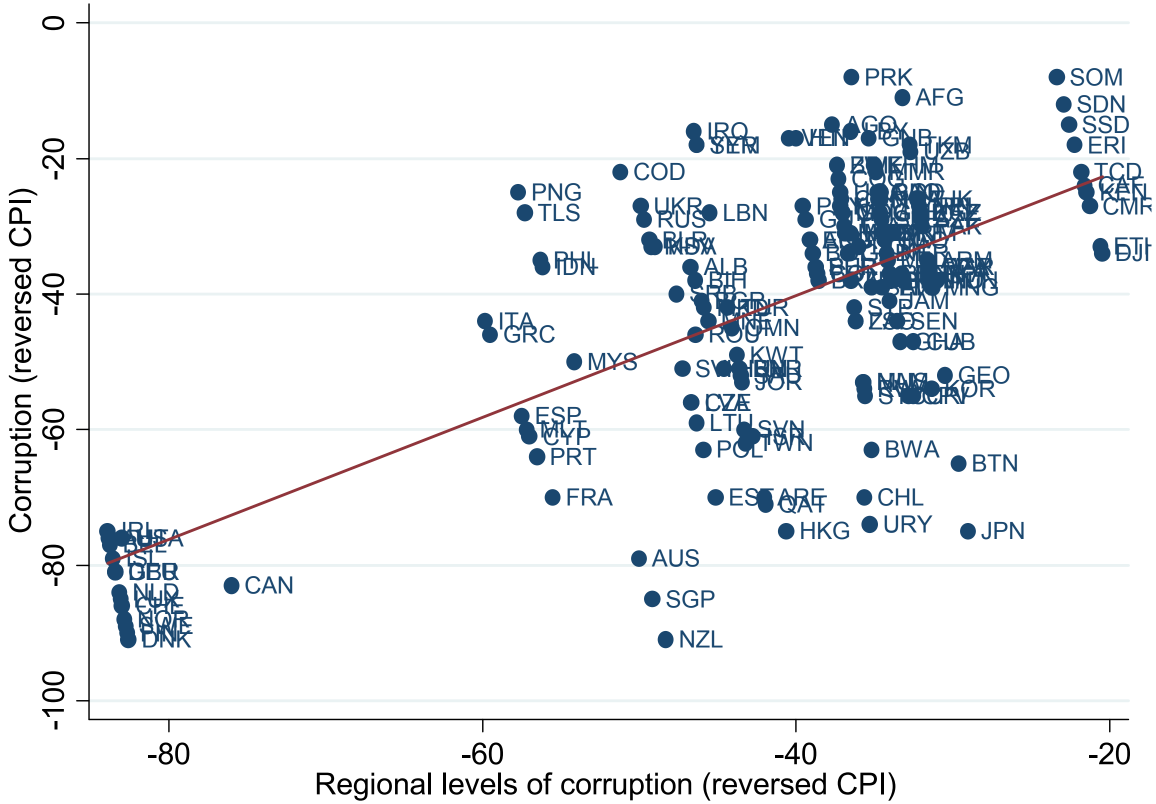
Notes: The figure shows the correlation between two measures of corruption: The reversed CPI and the corruption sub-component of the ICRG. The sample of country-year observations for which both indicators are available consists of 795 data points, the correlation is 96.05%.

Figure 4: Non-Parametric Estimations on the Relationship between Corruption and Economic Growth, Reversed CPI versus ICRG (Corruption Sub-Component).



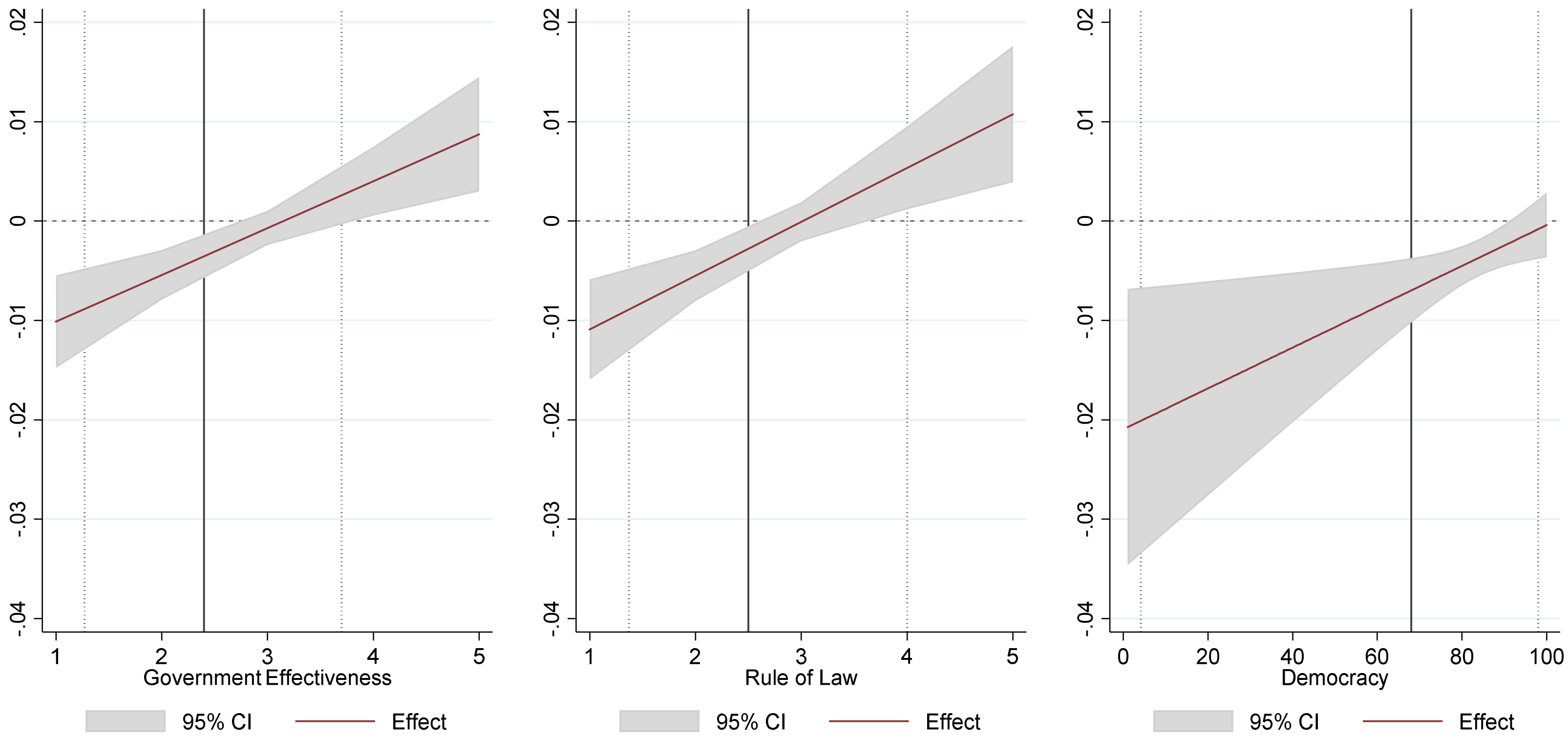
Notes: The figure shows non-parametric estimations on the relationship between corruption and economic growth using both the reversed CPI (left panel) and the ICRG (corruption sub-component; right panel) as measures for corruption. Estimates use kernel-weighted local polynomial smoothing with Epanechnikov kernel.

Figure 5: National Levels and Jack-knifed Regional Averages of Corruption.



Notes: Figure shows the correlation between national levels of corruption and jack-knifed regional levels of corruption for the year 2015, which is the middle of our sample. The figure is strongly comparable when analyzing other years in our dataset. The correlation is 66.9% in the year 2015 and 65.4% in the full sample of observations.

Figure 6: Marginal Effect of Corruption on Growth at Different Levels of Government Effectiveness, Rule of Law, and Democratization.



Notes: The figure shows marginal effects of corruption on economic growth, estimated at individual levels of government effectiveness, rule of law, and democracy. The red line shows the marginal effect, the surrounding grey-shaded area portrays the 95% confidence interval. The dashed grey-line displays the level of zero as a benchmark for significance. The graph is based on the model of Equation (3), reported in the reduce models (Columns 1, 3, and 5) of Table 7. The horizontal lines show the empirical distribution of government effectiveness, rule of law, and democracy. The dashed-lines (light gray) represent the 10th and 90th percentile of the distribution, the sold line (dark gray) shows the mean of the distribution.

Appendix

Table A1: Regression Results, Controlling for Confounding Factors. Dependent Variable: Real Per Capita GDP.

	Reduced	GDP Dynamics	Investment	Electoral Cycles	Fertility Rates	Democracy
	(1)	(2)	(3)	(4)	(5)	(6)
Corruption	-0.005***	-0.002**	-0.001*	-0.001*	-0.002*	-0.003**
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Log(GDP^{pc}) $(t-1)$		0.696***	0.857***	0.853***	1.001***	0.998***
		(0.135)	(0.085)	(0.086)	(0.323)	(0.322)
Log(GDP^{pc}) $(t-2)$		0.0703	-0.385***	-0.387***	-0.590*	-0.585*
		(0.060)	(0.081)	(0.080)	(0.327)	(0.326)
Log(GDP^{pc}) $(t-3)$		0.058	0.219***	0.226***	0.297***	0.293***
		(0.061)	(0.083)	(0.083)	(0.106)	(0.107)
Log(GDP^{pc}) $(t-4)$		-0.049	-0.026	-0.033	-0.032	-0.0248
		(0.051)	(0.061)	(0.059)	(0.056)	(0.057)
Investment			-0.002	-0.002	-0.002	-0.002
			(0.003)	(0.003)	(0.003)	(0.003)
Election year				0.004	0.003	0.003
				(0.002)	(0.003)	(0.003)
Log (Fertility Rate)					0.108	0.117
					(0.070)	(0.071)
Democracy						0.022*
						(0.012)
Observations	1,194	1,192	562	562	346	346
Countries	175	175	135	135	130	130
R-Squared	0.171	0.654	0.750	0.751	0.666	0.669
F Stat	13.10	181.8	81.08	81.46	55.16	52.37
F p-val	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table reports effects of corruption on economic growth when we control for growth determinants that potentially confound the relationship between corruption and growth. Cluster-robust standard errors reported in parentheses, each model includes fixed country and period effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$