

LUND UNIVERSITY School of Economics and Management

Corruption Kills

A Panel Data Analysis of OECD Countries

by

Per Jonas Partapuoli

Emma Stanley

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Abstract

This paper studies the effect of corruption on four selected health outcomes, by using crosscountry panel data, containing the 36 member states of OECD. The time period stretches from 1995 to 2017, extending upon previous studies by including data from more recent years. In order to estimate the effects of corruption, the paper uses Ordinary Least Squares, fixed effects and two-way fixed effects methods. In addition, we employ a Two-Stage Least Squares estimation method to check the robustness of the findings. To measure corruption, the main index used is the reasonably new Bayesian Corruption Index (BCI). Moreover, the paper investigates if the choice of corruption index has any effect on the results by using two additional measures of corruption; Corruption Perception Index (CPI) and Control of Corruption Index (CCI). The paper concludes that (1) increased levels of corruption tend to increase infant mortality rates and child mortality rates while corruption has no significant effect on neonatal mortality rates and life expectancy in OECD countries, (2) using BCI as corruption index generates results similar to previous research and (3) using three different corruption indices generate different results, which proves that the choice of index does matter. These findings confirm that corruption indeed kills and that a reduction of the level of corruption would improve public health globally.

Keywords: Corruption, Health, Mortality, Life expectancy, Bayesian Corruption Index, OECD

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List of abbreviations

BCI	Bayesian Corruption Index
CCI	Control of Corruption Index
CPI	Corruption Perception Index
DFID	Department for International Development
DPT	Diphtheria, Pertussis (whooping cough), and Tetanus
FE	Fixed Effects Model
IMF	International Monetary Fund
IV	Instrumental Variables
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
QoG	Quality of Governance
TI	Transparency International
USD	US Dollars
VIF	Variance Inflation Factor
WHO	World Health Organization
WGI	Worldwide Governance Indicator
2SLS	Two-Stage Least Squares

1 Introduction

On April 18th, 2019, the subscribers of Wall Street Journals could read about an immense American federal sting operation. 31 doctors, eight nurses, seven pharmacists, dentists, and other healthcare professionals were arrested for the distribution of over 32 million prescriptions of addictive painkillers, consisting of opioids; an active substance in drugs such as morphine, heroin, and opium. In exchange for cash, doctors prescribed pre-signed prescriptions while dentists performed unnecessary dental care such as teeth extractions to get a legal reason for prescribing opioid pills to clients (Singer, 2019). In May 2019, the founder of an American pharmaceutical company, was convicted for bribing doctors to prescribe opioids to patients, not in need of the pills (BBC, 2019). These cases of corrupt actions and prescriptions of opioids have induced a new epidemic crisis in North America, where more than 400 000 people have died since 1999, in the US alone, from overdosing opioids (Scholl, Seth, Kariisa, Wilson & Baldwin, 2019). Prescribing drugs in exchange for money is only one of the many forms of corruption in the healthcare sector existing worldwide, causing addiction, economic losses, and deaths.

As illustrated, corruption is an increasing problem, both in emerging and advanced economies. Corruption affects society in various ways, and the healthcare sector is particularly exposed (Vian, 2008). Every year, approximately USD 3 trillion are spent on healthcare globally (Hussmann, 2011). This makes healthcare a prone target for abuse, where a large amount of capital directed to the health sector tends to disappear every year before even being assigned from the government budget. United States is one of the countries that spend the most money on healthcare, about 15.3 percent of GDP. Nonetheless, according to the two major US public healthcare programs, Medicare and Medicaid, 5-10 percent of the budget is estimated to be lost to "overpayments" (TI, 2006).

According to Transparency International (TI, 2006), corruption deprives people's access to primary healthcare. Besides, it leads to incorrectly administered treatments and may result in cases of death. Corruption is also believed to undermine a country's ability to reach economic growth (IMF, 2016). A new study by the IMF displays how restrained corruption could convey additional tax revenues across the world, to a value of USD 1 trillion annually. Instead of being

lost to corruption, this money could have been invested in needed healthcare, infrastructure, or education, which all would improve economic growth (TI, 2019). According to Bloom, Kuhn and Prettner (2018), there exists a strong positive relationship between health and income. Countries with higher health levels tend to have higher income levels compared to countries with lower health status. This is yet another reason for the importance of reducing corruption, and to improve health status in the world.

Previous studies have investigated the relationship between corruption and health outcomes, mainly using perception-based indices as indicators of corruption. A study on aggregate country level produced by IMF (2016) shows that higher levels of corruption implies increased infant mortality rates, i.e., when the infant dies within the first year after birth. Similar results are found in the article by Li, An, Xu and Baliamoune-Lutz (2018), even after adjusting for education, health spending, and urbanization. The study shows how corruption increases mortality rates, including infant-, neonatal (when the infant dies within the first 28 days after birth)-, and child (under-five year) mortality rates while it reduces life expectancy measured in years and immunization rates. Further, public spending on education, health, and social protection is reduced due to corruption, while the quality of care is directly affected by corruption in financial management (Hussmann, 2011).

The overall aim of this paper is to investigate if corruption kills, through its effect on infant-, neonatal-, and child mortality rates, and life expectancy at birth, in order to further develop the existing literature. Moreover, a specific aim of the study is to examine if the choice of corruption measures matters for the results. This study will contribute to the existing literature by delimit the sample to the 36 member states of OECD while extending the time period to include data from 1995 to 2017, which is the most extensive time period used so far. Unlike previous research, we contribute by studying the effect of corruption with the relatively new and unexplored measure of corruption, BCI, which is not perception-based and has sparsely been used before. To test the robustness of the outcomes of the study, and if the choice of measure of corruption matters, two additional measures of corruption, that are perception-based, will be introduced.

From using OLS, fixed effects and two-way fixed effects, and 2SLS estimation methods for robustness, the study finds evidence of that increased levels of corruption implies higher infantand child mortality rates. This confirms that corruption kills and that a reduction of corruption could improve the overall health outcomes in the member states of OECD. Nevertheless, the results are not entirely consistent with previous studies since the effect is not as widespread among the different health outcomes as previously reported. For neonatal mortality and life expectancy, the study finds close to no significant estimates of corruption using BCI. Further, from the robustness checks, the paper has found that the effects of using BCI or one of the perception-based indices, CPI, as measure of corruption are somewhat similar, although the magnitude of the effects differ. Conversely, the effects of using the other perception-based corruption measure, CCI, is distinct to both BCI and CPI. This finding indicates that the choice of corruption measure does have an impact on the empirical results, contradicting the findings by previous researchers, where many have stated that the results from using different corruption measures do not vary significantly.

The remainder of this paper is organized as follows. The second section presents the background to build a foundation of knowledge to the study. It also includes the theoretical framework on which the study is based, and a literature-, and a methodological review from previous studies. The third section presents the methodology and introduces the data, and descriptive statistics together with the variables of interest. The fourth section presents the empirical results and the results from the robustness checks. The fifth section discusses the findings and the sixth, and the last section concludes the paper.

2 Background

This section will provide a foundation for the study by introducing corruption and presenting the theoretical framework. It will also illuminate what the literature have found, and the methodological methods for the investigation.

2.1 Corruption

What is Corruption?

Corruption is an ambiguous term that refers to everything from paying bribes to civil servants, to broader economic and political crimes that are considered as an abuse of power. It often involves the use of public funds for private benefit and diverting scarce funds. There is no universally accepted definition. Thus, this paper will use the most commonly used definition of corruption provided by TI (2018a), which states that corruption is "the abuse of entrusted power for private gain". Although the definition is rather simple, the meaning is, however, much more complicated. Usually, one can classify corruption into several entities depending on the type, amounts of money involved, and in which sector it occurs. Generally, there is a distinction between grand and petty (bureaucratic) corruption. Grand is a more severe form of corruption since it includes the highest level of the political sphere where large amounts of money and policy manipulation are at risk. Petty corruption is mainly what the general public experiences in interaction with, e.g., public officials like the police, and hospital officials, that abuses entrusted power placed under their authority (TI, 2018a).

Measuring Corruption

Corruption is hard to measure accurately. New indices have in recent years been developed, trying to handle the complexity of corruption. One of the most recent indicators for corruption is BCI, which is not perception-based in contrast to many other corruption indices. BCI is measured on a scale from 0-100, where 0 is totally "clean" from corruption. The leading indicator of corruption in the public sector, CPI, is, however, perception-based (TI, 2018b). CPI is far from the only existing perception-based corruption indicator, and it is, therefore, vital to

keep in mind that the results possibly will vary depending on the indicator and that there is not an unanimous voice on which indicator of corruption to use in quantitative research. Studies have shown that indices can affect the empirical results in research such that it is misinterpreted, especially when using perception-based indices. This is due to the influence of how many cases of corruption that people can observe or potentially observe (Bardhan, 2006). It is also unclear whether perception-based corruption indices are possible to compare across countries (Banerjee, Mullainathan & Hanna, 2012). Another disadvantage that a study by Abramo (2008) shows through a cross-country study of 60 cases is that perception of corruption does not necessarily explain the experience of corruption since the trend of other opinions can influence the perception.

What does Corruption Cost?

Corruption in society is costly, and in worst cases, it costs lives. It directly affects people's freedom, wealth, and health. The different levels on how corruption erode a society, have been categorized into political, economic, social, and environmental. Briefly, one can say that democracy, national wealth, trust, health and welfare, and ecological systems are at stake when corruption is present. It is hard to estimate how much corruption costs, since the phenomenon occurs in everyday life, both in emerging and advanced economies. Based on an extrapolation by Daniel Kaufmann in 2015, bribery alone was estimated to cost between USD 1.5 to 2 trillion, which is almost 2 percent of the global GDP. Yet, it is just one of many forms of corruption (IMF, 2016). Globally, one of four people asked, state that they have paid bribes for public services, while, in the EU alone, this amounts to 9 percent of the households asked (Pring, 2017).

Corruption in the Health Sector

Corruption in the health sector affects all parts of the healthcare chain, including the healthcare market. This is a great source for making large profits for companies due to an aging population and increased health expenditures, triggering behavior on using unorthodox methods to increase revenues. Vian (2008) identifies opportunities for pharmaceutical companies to bribe professionals and politicians, for their influence of winning bids for supplying medical devices. Multinational companies such as Johnson & Johnson and Medtronic have been involved in bribery of health officials, especially subjecting emerging countries. Many cases of bribery have also been prosecuted under anti-bribery laws in OECD countries. A few years ago, one of the largest pharmaceutical manufacturers, Pfizer, agreed to pay a fine on USD 60 million to

settle potential violations against anti-bribery laws for suspicious payments to health officials in Italy and Croatia, among several countries (Mackey & Liang, 2012). More recently, over 40 companies have been sued in Canada for involvement in the manufacture, distribution, and wholesale of the addictive painkiller opioids. The minister of mental health and addictions in British Colombia stated that the suit aims to cover costs of increased public healthcare caused by companies' "negligence and corruption" (Britten, 2018).

The perception of corruption in the health sector is rather high, the global average of experiencing the sector as corrupt, is about 45 percent. In OECD countries, one-third of the citizens have stated that they experience the health sector as corrupt or very corrupt. There is yet some variation among the OECD countries, where half of the population in Greece, Slovak Republic, Italy, and Chile believe the health sector to be corrupt or very corrupt, whereas the population in Denmark and New Zealand believe it to be just above 10 percent (OECD, 2017b).

Most OECD countries are advanced economies with democratic governments. This provides reasoning to why many would think that corruption is not as widespread among OECD member states, but as illustrated above, this is not entirely true. The OECD countries together reached a BCI average of about 30 during the time period 1995 until 2017, which is lower than the world average. However, studies from Eastern Europe show that it is not unusual with "under the table" payments to health providers (Holmberg & Rothstein, 2011). Corruption might thus be found in many different forms and might be harder to spot in OECD countries. Also, it is proved that corruption has a corrosive impact on the population's level of health. Therefore, it is of great importance for society to find a way to tackle corruption to receive better health outcomes.



Figure 1: Level of corruption in OECD 2017

The figure illustrates the corruption measured in BCI (from 0-100) for OECD countries. The lowest estimates are for Finland and New Zealand, and the countries are rather "clean" from corruption. The highest estimate is for Mexico, suggesting it to be fairly corrupt.

2.2 Theoretical Framework

As stated above, the healthcare system is particularly inclined to corruption. This is because the sector is distinctly characterized by a mix of uncertainty, asymmetric information, and a large number of actors involved. All together, these characteristics create opportunities for corrupt and fraudulent behavior, working as a systematic feature. Thus it is difficult to ensure transparency or trustworthiness that could hinder such a feature. Moreover, the healthcare sector is especially exposed to corruption since society involves private actors to execute critical public functions, such as providing health insurance and pharmaceutical distribution. In addition, the healthcare sector involves a large amount of public funding. The collective spending on health services among the European countries of OECD exceeds USD 1 trillion annually, and the US alone spends USD 1.6 trillion (Savedoff & Hussmann, 2006).

The three features, i.e., uncertainty, asymmetric information, and a large number of actors, were first introduced by Kenneth Arrow in 1963, and many would say that it created the foundation of health economics. Savedoff and Hussmann (2006) illustrated how this is linked to corruption

with a prevalent figure (see figure 2), which has recurrently been used in the existing literature. The authors argue that the uncertainty in the healthcare sector creates market failure, such that medical care and insurance markets are inefficient. One of the arguments for uncertainty is that people usually do not know when they become ill, or even that they are ill. If they seek medical care and get treatment, it is difficult to know if the recovery is due to the treatment or not. Such that the prescribed pills, e.g., antibiotics, may not even work and the body itself handles the actual recovery. In those cases, the patient cannot hold the medical provider or the pharmaceutical manufacturer into account.

According to Savedoff and Hussmann (2006), the second feature in the healthcare sector is asymmetric information. The patient is less informed about the technicalities in the healthcare system than, e.g., the doctors. The doctors are less informed about the substances active in pills than pharmaceutical manufacturers. As such, the information among the actors is not equal, which has been illustrated as a "principal-agent problem". Here, the patient wants the doctor to provide some kind of treatment but the interests could differ, and the patient might not get all the information for correcting the treatment.

The third feature is that a large number of actors are involved in healthcare. Savedoff and Hussmann (2006) divide these actors into five main categories: government regulators; suppliers; payers; providers; and patients. The existence of these actors in one sector makes it difficult to identify corruption and keep transparency, which increases the opportunities for fraud, bribery, informal payments, theft, or misuse of health equipment. One can also argue that when many actors are involved in a sector, there is a need for trust in each other, in order for the sector to function. Thus, trust may be one of the mechanisms that affect health outcomes. Holmberg and Rothstein (2011) study how corruption affects health outcomes through the quality of governance for a country. They find that trust indeed may be a mechanism. Lower quality of governance levels implies that people put less faith in their governance and are not willing to pay enough taxes as a result of not being confident in where the money end up. This would lead to less economic resources possessed by the state, fewer resources being assigned to the healthcare sector, which in turn could be a major causal factor to lower health levels. Kassirer (2006), as well as Factor and Kang (2015), also provides reasons why the health sector is sensitive to corruption. One of their conclusions is that corruption tends to be more present when the public and private sector meets, which has also been seen in other industries.



Figure 2: The five main actors in the healthcare sector and the opportunities to corruption. Source: Savedoff and Hussmann (2006).

Figure 2 summarizes the three features by illustrating how corruption may occur and what directions it may take in the healthcare sector. All actors may be exposed to corruption as well as acting corruptly themselves. The uncertainty that exists within the sector creates an opportunity for governments to take on the role as protectors of their citizens, through providing supervision and information, and verifying medications and procedures. However, this leads to openings for suppliers (e.g., pharmaceutical research companies) to bribe governmental supervisors to accept applications while providers may try to get supervisors to overlook the need of licenses by bribes, or other forms of corrupt actions. Suppliers (e.g., suppliers of medical equipment) have most information and knowledge of their products, which is a benefit for corrupt actions. They can bribe providers such as doctors and other healthcare staff to prescribe their pharmaceuticals (as in the opioid crisis case) and sell overpriced or re-packed expired products. Patients may also act in corrupt manners by lying about insurance plans or income levels to get free healthcare. However, patients are the actors that suffer the most from

corruption, and may be exposed to overpricing, informal payments, or receiving unnecessary treatment by doctors, in turn affecting the individuals' health.

2.3 Previous Studies

Under this subsection, studies that have investigated the effect of corruption on different measures of health outcomes will be presented. Furthermore, a review of the methods used throughout the literature is presented. The last part will summarize the previous findings.

2.3.1 Literature Review

A recent study by Li et al. (2018) examines how corruption affects health outcomes for 150 countries between 1995 and 2012. The article finds that various mortality rates for child specifications are significant and negatively correlated with CPI, indicating that corruption increases mortality rates and reduces life expectancy and immunization rates. The authors also argue that reducing corruption should imply positive effects on mortality rates, i.e., a reduction, and also improved health outcomes overall. Further, they show that poorly governed countries do not confirm any signs of improvements in health outcomes from increasing public spending since the effect of public spending is small and insignificant.

Gupta, Davoodi and Tiongson (2000) show with cross-sectional data using OLS and 2SLS models that countries with high corruption also have one-third higher child (under-five year) mortality rates than countries with low corruption. They also conclude that increasing health spending does not necessarily improve health outcomes, while reducing corruption itself will most likely reduce infant- and child mortality. Factor and Kang (2015) have similar findings in their study, consisting of 133 countries. They state that corruption has a strong effect on health outcomes by delivering poorer health outcomes globally and that higher levels of corruption will generate a lower share of GDP per capita being assigned to health expenditure. This suggests that a reduction in corruption would increase health expenditures. However, alongside this finding, they do not seem to find any significant direct association between health spending and health outcomes when controlling for other factors.

Other researchers have specifically investigated the effect of public spending on health. Rajkumar and Swaroop (2008) study the effect of public spending on social developing outcomes at different levels of governance, measured by the level of corruption and quality of bureaucracy. This is of interest since it may be argued that increased public spending on, e.g., healthcare does not necessarily lead to desirable outcomes if the institutions are malfunctioning. The authors used a dataset consisting of 91 countries over three years and find that a higher share on public spending decreases the rate of child (under-five year) mortality in countries that are suggested to have good governance. They propose two possible explanations to why public spending might not be efficient nor generate desirable outcomes; either an increase in public spending will only decrease private spending on health or education; or, there is a leakage in public spending and unsteady institutional capacity. Rajkumar and Swaroop (2008) find that the effect of an increase in public spending will depend on the level of governance. A country with good governance that increases health spending relative to GDP with one percent will decrease of 0.20 percent, while in countries with low governance, there is a non-existing relationship with the child mortality rate.

Quality of governance is, thus, an important factor when discussing corruption and its effect on health outcomes. With a cross-sectional dataset, Holmberg and Rothstein (2011) perform a study on how the quality of governance affects health outcomes in 120 countries by controlling for corruption, and governance effectiveness. They use basic econometric methods since it first and foremost is an article within the political science field. One of the hypotheses in the article is that better economies lead to better health outcomes. Thus, in one part of the study, they classify the sample into (rich) OECD countries and (poorer) non-OECD countries as a proxy for economic development and wealth. The results show that in emerging economies, a vast majority have experienced corrupt practices in the health sector, while corruption in rich countries, such as the majority of the OECD countries, takes another form, like overbilling. The authors find that there is a positive relationship between quality of governance and longer life expectancy, and lower levels of mortality rates among children and mothers. The article shows that the low quality of governance has a negative impact on population health, while private spending has not.

Thus, the effect of corruption on public spending seems to generate mixed results. An article by Swaleheen, Ali and Temimi (2019) studies the effect of corruption on public spending for health and education and find that it is significant and non-linear for the sample consisting of

134 countries observed over two decades. They find that corruption has a positive effect on the share of public resources spent on public health. The partial effect of corruption was very high for only 16 countries, showing a negative effect of corruption on health expenditure.

The shared opinion in these studies is that increasing corruption will deliver poorer health outcomes. A political tool to deal with failing health outcomes could be the reduction of corruption itself. Reports from WHO (Parry, 2006), DFID (Hussmann, 2010) and U4 Issue (Hussmann, 2011) draw the same conclusion. In order to prevent corruption in the health sector, Mackey and Liang (2012) argue that efforts need to be coordinated. There have been taken measures by reforms to monitor more thoroughly, however on the individual state level. The authors claim that there is not enough of a comprehensive and internationally cooperative framework that deals with corruption in the health sector.

2.3.2 Methodological Review

Most papers in the existing quantitative literature examine the impact of corruption on health outcomes, by using panel data with an OLS estimation method, except for Factor and Kang (2015), who use a structural equation model for two years. Many of those with a simple OLS approach do not take into consideration that an adverse causality problem may occur. One of the most recent articles states that many papers do not consider the econometric challenges when investigating the effect of corruption, by ignoring unobserved country-specific heterogeneity, endogeneity, and non-stationarity (Swaleheen, Ali & Temimi, 2019). In recent years, studies have included an additional fixed effects approach to address omitted variables caused by country-specific effects or time-specific effects (see, e.g., Lio & Lee, 2016, and Li et al. 2018).

To isolate the effect of corruption on health, most of the articles control for social, infrastructural, and economic factors. According to Collier (2002), there is an additional factor that may give rise to corruption, which is the political and legal condition. The three main domains as such, according to Dr. Collier, are socio-cultural, economic, and political and legal conditions. Although, the last domain, such as the rule of law, accountability, and democracy score, is not as frequently included as a control variable. Within these factors, some of the control variables are basic drinking-water services, population using safely managed sanitation services, DPT-, and measles immunization. Conversely, these variables do not vary noticeably for OECD countries, and as such, are not in the interest of this paper.

Most of the previous research is investigating the effect of corruption on health outcomes by using either CPI or CCI as measures of corruption. Ko and Samajdar (2010) have studied the reliability of international corruption indices and concluded that reliability has increased over the years. However, there are risks such as selection bias and measurement errors that researchers should be aware of. Therefore, the authors suggest that empirical analysis should be further analyzed to minimize the shortcomings of corruption indices by using several indices from different institutions.

Moreover, previous literature have discussed problems of potential endogeneity. The endogeneity problem can cause estimation bias since both corruption and health might be correlated with unobservable factors in the error term. It is not unlikely that people with poorer health are keener on paying bribes to receive services that they otherwise would not have had access to. Additionally, an inept government may ignore providing healthcare to their citizens while having officers who are devoted to rent-seeking and corrupt activities (Lio & Lee, 2016). To deal with this potential problem, some researchers have adopted instruments and a 2SLS approach to their studies (Rajkumar & Swaroop, 2008; Lio & Lee, 2016; Li et al. 2018). Two necessary conditions need to be satisfied for an instrument to be valid: 1) the instrument has to be correlated with corruption; and 2) it has to be exogenous to the health outcomes (Wooldridge, 2009).

Lio and Lee (2016) adopted two instrumental variables and have performed thorough tests, including a test of endogeneity, a weak instrument test, and an over-identification test. First, they include a country's democracy score taken from the Polity IV Dataset and secondly a measure of whether a country exports fuel, in accordance with the designation of the World Development Report. Several previous studies have proved that democracy has an impact on reducing corruption (Triesman, 2000; Goel & Nelson, 2005) while abundant natural resources seem to cause corruption by creating opportunities for rent-seeking activities (Leite & Weidmann, 1999). Hence, both these measures tend to be correlated with corruption while according to Lio and Lee (2016), it is reasonable to assume they have no direct effect on health.

Li et al. (2018), however, criticizes the instruments of Lio and Lee (2016), since they mean that democracy can directly affect health outcomes. Thus, they instead use the corruption score lagged two periods as an instrument for corruption at the current period. This instrument is argued to be strongly correlated with current corruption while not affecting current health outcomes. Still, Li et al. (2018) are only implementing a first stage estimation of their

instruments and do not control for the validity of their instrumental variables nor if endogeneity is a problem in their study. One can debate whether the criticism is legit since they do not adjust the IV/2SLS approach with a full alternative solution that can be tested.

2.3.3 Summary of Previous Studies

Throughout previous literature, studies have proved that corruption has a negative effect on health outcomes worldwide. All research seems to be somewhat unanimous in that a reduction of corruption is needed to reduce mortality rates and increase life expectancy. Most existing literature have in common that they use large samples, almost always consisting of more than 100 countries. Despite the already existing research on how corruption affects health outcomes, only one article, to our knowledge, has partly focused on how corruption affects the health sector solely in advanced economies such as OECD countries. However, thoroughly econometric methods are missing in this study, and Holmberg and Rothstein (2011) are only using a cross-sectional sample, not investigating the effect over time. Therefore, in the remainder of this paper, we will simulate tests that have been found in previous literature, focusing on the member states of OECD for a more extensive time period than earlier studies. As a robustness analysis, this paper will also use, and develop, the instruments employed by Lio and Lee (2016) as well as Li et al. (2018), to investigate whether these would work for OECD countries, in the same way as previously has been argued.

3 Methodology

In this section, the methodological strategies to study the relationship between corruption and the different measures of health outcomes will be presented. The section will also cover the data used and how the dataset was constructed. Furthermore, descriptive statistics, the interpretations of the variables, and an outline of the sources to the data are presented.

To investigate how corruption affects health outcomes, this paper will use three empirical methods that have been identified in previous literature. Most of the quantitative studies in the field aim to affirm the influence of corruption on health by using OLS regressions without additional methods to distinguish the direction of causality. Hence, one of the models is an OLS for panel data, or more precisely, a pooled OLS model. However, this will not deal with the time- and country invariant variables that could be correlated with health outcomes, i.e., mortality rates and life expectancy, and corruption. Therefore, the general model will address the problem of omitted variables by employing a two-way country- and time period fixed effects approach. The effect of corruption on health is not straightforward and may be complicated due to potential endogeneity problems with the corruption measure. Therefore, the third approach is a 2SLS model where instruments will be used on corruption to measure the effect on health outcomes, and will function as a robustness check in the study. Also, we will test the data for heteroscedasticity and multicollinearity.

3.1 Model Specification

The equation for the general model of this study is the two-way fixed effects model, specified as follow:

$$Health_{it} = \alpha + \beta * Corruption_{it} + \gamma * X'_{it} + \delta * D'_t + \mu_i + \varepsilon_{it}$$
(1)

The dependent variable, $Health_{it}$, is the vector of health outcomes for country *i* at time *t*. It consists of infant mortality rate (dying before reaching the age of one), neonatal mortality rate (dying within the first 28 days), child mortality rate (dying before reaching the age of five), all

of which counted per 1 000 live births. The fourth and final health outcome used is life expectancy at birth measured in years. Corruption is the main variable of interest and the primary explanatory variable, measured by the BCI, which is also specified for country *i* at time *t*. X_{it} is a vector of exogenous control variables and D_t is a time-specific effect that affects all countries in case of a shock. μ_i captures the country-specific effects, which are time-invariant unobserved country characteristics, such as geographical conditions, climate, and culture. Finally, the country- and time specific error term, ε_{it} , captures all factors that may affect mortality rates or life expectancy without being included in the model.

The methodological strategy for this paper is first to study the bivariate relation to get the effect of corruption on health by running a restricted OLS model, excluding all control variables, X_{it} , and the time- and country-specific effects, D_t and μ_i . This provides an overview of the effect of corruption on health without anything else absorbing the effect from corruption.

The first model is unable to identify potential bias in the estimates arising from time-invariant variables. Therefore, the second restricted model will be specified such that the country-specific effects that persist over time are captured; normally, quantitative research refers to this as the fixed effects model. Thus, adding μ_i to the equation in the first model will allow for comparison on how the fundamental effect of corruption on health changes from using an OLS to a fixed effects model, ceteris paribus.

One challenge when estimating the causal relationship between corruption and the health outcomes of interest is to separate the effect of corruption from other factors that may have an impact on the different health outcomes. Hence, by expanding the second restricted model, and including the vector of exogenous control variables, X_{it} , the preciseness of the estimates will be improved. Here, the control variables are categorized into three groups that have been frequently used in previous studies, namely social, infrastructural, and economic variables (see Gupta, Davoodi, & Tiongson, 2000; Rajkumar & Swaroop, 2008; Lio & Lee, 2016; and Li et al. 2018). The order of how the controls will be added to the model is based on previous research, where the first added cluster of controls may not explain how corrupt the health sector is. The first cluster of control variables is thus the social factors, i.e., mean age of mother at childbirth, ethnical-, linguistic-, and religious fractionalization as control variables. The same idea applies to the following factors. The second group of control variables to be added to the models is the infrastructural factor, i.e., urbanization. The third and last group of control variables to be added to the models is the economic factors, which are GDP per capita, total

health expenditure as a share of GDP and government health expenditure as a share of GDP. Additionally, the time-specific effect, D_t , is added as a time dummy. Therefore, these models will be specified such that the country-specific effects that persist over time are captured, namely a two-way fixed effects model, referred to as the general model specified in equation (1).

Using a two-way fixed effects method will imply that the effects that possibly will be correlated with both corruption and health outcomes are partialed out. The argument of proceeding the study with a two-way fixed effects model rather than a random effects model is based upon two motives. First and foremost, the assumptions for fixed effects models are more relaxed compared to random effects models and allow for the time-invariant unobservable variables to be correlated with corruption. Relaxing the assumption is more realistic in this case since it is likely that unobservable variables such as culture, land area or historical influences are correlated with corruption (Seleim & Bontis, 2009; Goel & Nelson, 2010). Second, some previous studies have used a fixed effects model, which makes it a relevant model for this study to employ.

3.2 Robustness Analysis

To see if the results from the main analysis are robust, there is a need to include appropriate tests. One as such is to use several data sources for corruption, and control for these measures. Accordingly, this paper will employ two other corruption measures, which frequently occur in the literature, namely CPI from TI and CCI from the World Bank. To investigate whether the effect is dependent on the corruption measure, this paper will perform identical tests to the main regressions. This by using OLS and two-way fixed effects models, including all control variables for both tests, with CPI and CCI as explanatory variables instead of BCI.

Furthermore, there is a need to consider that the data over corruption and health could suffer from endogeneity problems, which has been discussed frequently in previous literature. For this paper, that would imply that corruption is correlated with unobservable factors included in the error term. Therefore, we will conduct 2SLS for each dependent variable and corruption measure, formulating the following models:

$$Corruption_{it} = \theta + \psi * Instrument_{it} + \gamma * X'_{it} + \delta * D'_t + v_{it}$$
(2)

$$Health_{it} = \alpha + \beta * Corruption_{it} + \gamma * X'_{it} + \delta * D'_t + \varepsilon_{it}$$
(3)

Equation (2) is the predicted effect of corruption from the instrument. From this, we continue with the second stage in the 2SLS by replacing corruption with the predicted effect of corruption to the causal effect of interest found in equation (3). This will imply that the instrument affects health through corruption; meanwhile, not having a direct effect on health outcomes itself.

This paper will use the same instruments as Lio and Lee (2016), i.e., instrument corruption with democracy score and export of fuel as a percentage of total merchandise export. By including a democracy score as an instrument, we include the political and legal domain that is said to give rise to corruption and thus also use all three factors of Collier (2002) in this study. Secondly, we will use the instrument of Li et al. (2018) and instrument corruption with a two-period lag. To be able to check the validity of the instrument, there is a need to have at least two instruments to one endogenous variable. Therefore, a three-period lagged corruption measure as an instrument. The motivation by Li et al. (2018) of why corruption lagged two periods could work as a valid instrument is also applicable to the three-period lag.

3.3 Data

To conduct the analysis, we have compiled a panel dataset consisting of indicators for corruption and health outcomes together with social, infrastructural, and economic factors from various databases. The dataset consists of yearly data from the 36 member states of the OECD as of July 5, 2018. The OECD is an organization that mainly aims to stimulate economic development and world trade, and the member states are fairly homogenous, both in terms of access to basic resources (e.g., water and sanitation) and governance. In addition, the majority of the member states are high-income economies, and in 2017, the OECD member states comprised of roughly 62 percent of the global nominal GDP (The World Bank, 2019a). For a list of all member states, see figure 4 in appendix A. The OECD is also is one of the most reliable sources for economic and social data. They monitor and collect data, do analyzes and forecasts in a broad range of public policy areas, e.g., agriculture, education, health, environment, and trade (OECD, 2017a). This motivates the choice of solely focusing on OECD countries, combined with the fact that this delimitation is not common in the existing literature.

The data is limited to the time period 1995-2017, which is one of the most extensive time periods studied to date. The reason for using this time interval is that the perception-based indices were founded in 1995 and 1996. Additionally, this was the time period for which there exist variables for a sufficiently complete dataset. Since the study aims to investigate the effects of corruption on health, a corruption index within the health sector should be used as an explanatory variable. As far as we are concerned, there exists no such measure yet. Thus, the study uses three different general corruption indices as proxies for corruption in the healthcare sector. It should be noted that the Gini coefficient is not included as a control variable in this study. The reason for not including the Gini coefficient as a control variable is that there is a large number of missing observations, and since OECD changed the methodology for measuring the Gini in 2012, it would become difficult to compare with observations before and after 2012. Another reason is that most of the previous studies do not employ income distribution at all. Rajkumar and Swaroop (2008) even find the Gini to be insignificant in this coherency.

To get a somewhat easily foreseeable view of the effect of corruption on health outcomes, figure 3 presents the correlation between the variables in four graphs.



Figure 3: Relation between BCI and health outcomes

According to figure 3, higher levels of corruption implies higher mortality rates and shorter expected lifetime measured in years. The effect is consistent regardless of the usage of BCI or CPI, only varying in the magnitude of the effect (for CPI, see figure 5 in appendix A). Among the three different mortality measures, the impact of corruption is most significant on child mortality, and a one-unit increase in mean BCI implies a raised mean child mortality rate with 22 children per 100 000 live births.

3.3.1 Descriptive Statistics

Table	1:	Summary	statistics
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Variable	Definition	Mean	St. Dev	Min	Max	Obs.
Dependent variables:						
Infant mortality rate	Mortality rate of infant, i.e., dies within the first year, (per 1000 live births)	5.628	4.643	1.6	42.8	828
Neonatal mortality rate	Mortality rate of neonatal, i.e., dies within the first 28 days, (per 1000 live births)	3.63	2.717	0.9	25.2	828
Child mortality rate	Mortality rate of children, i.e., dies within five years, (per 1000 live births)	6.788	5.65	2.1	54.8	828
Life expectancy	Total life expectancy at birth, (years)	78.057	3.32	66.391	83.985	792
Corruption measures:						
BCI	Bayesian Corruption Index, (0 to 100, where 0 is clean from corruption)	30.353	14.853	6.45	60.545	824
СРІ	Corruption Perception Index, (0 to 100, where 100 is clean from corruption)	68.598	18.653	27	100	801
CCI	Control of Corruption Index, (-2.5 to 2.5, where 2.5 is clean from corruption)	1.118	0.919	-1.13	2.47	684
Control variables:	1 /					
Social						
Mothers age	Mean age of mother at childbirth	29.406	1.311	25.5	32.1	717
Ethnic	Ethnic fractionalization ^a	0.252	0.194	0.002	0.712	828
Linguistic	Linguistic fractionalization ^b	0.241	0.195	0.002	0.644	828
Religious	Religious fractionalization °	0.419	0.229	0.005	0.824	828
Infrastructural						
Urban Population	Urban population, (% of total population)	75.881	11.174	50.622	97.961	828
Economic						
GDP	GDP per capita, PPP (constant 2011 international USD)	33971	14599.6	8283.85	97864.2	827
Health expenditure	Total health expenditure (% of GDP)	8.076	2.119	2.448	17.15	798
Governmental health expenditure	Governmental health expenditure (% of GDP)	5.847	1.689	1.449	13.974	797

^a Indicates the probability that two randomly selected individuals in a certain country do not belong to the same ethnic group. Defined by a combination of racial and linguistic characteristics. Ranges from 0 to 1 and a higher index imply more fractionalized societies.

^b Indicates the probability that two randomly selected individuals in a certain country do not belong to the same linguistic group. Ranges from 0 to 1 and a higher index imply more fractionalized societies.

^c Indicates the probability that two randomly selected individuals in a certain country do not belong to the same religious group. Ranges from 0 to 1 and a higher index imply more fractionalized societies.

Table 1 presents the descriptive statistics of all variables included in the study. For the 36 member states of OECD, the average infant mortality rate is measured to 5.6 per 1 000 live births during the time period subject for the study. For neonatal and child mortality, the average mortality rates are 3.6 and 6.8 deaths per 1 000 live births, respectively. As seen from table 1, the distribution of mortality rates vary significantly, illustrating how infant, neonatal, and child mortality rates range between 1.6 to 42.8, 0.9 to 25.2 and 2.1 to 54.8, respectively. The average OECD life expectancy is 78 years, which is approximately nine years longer than the global average, estimated for the period 1995-2017 (World Bank, 2019b). Both BCI and CPI have mean levels of corruption that are better than average levels of the scales. However, the results are far from good, which confirm earlier statement that corruption indeed is present in OECD countries.

3.3.2 Variables of Importance

Dependent Variables: Child mortality and life expectancy

When analyzing health outcomes, one of the most commonly used measurements is mortality rates for infants and children. This is because it is a very precise measurement where few errors occur. According to Mishra and Newhouse (2009), infant mortality is a commonly used estimate of health in developing countries. Unlike life expectancy, the measure is not based on predictions but objective empirical data. The first child mortality measure, infant mortality, measures the number of infants that die before reaching the age of one year. The second child mortality measure is concerning neonatal mortality, which measures the number of infants dying within the first 28 days of life. Child mortality is the third and final mortality measure, which measures the number of children dying within the first five years of life; the most sensitive state in a human's life. All three mortality estimates are measured yearly and per 1 000 live births. Life expectancy estimates the number of years a newborn infant could expect to live if the ruling patterns of mortality at the time of birth would remain constant over the lifetime. The data is extracted from the QoG Standard Dataset (Teorell, Dahlberg, Holmberg, Rothstein, Alvarado Pachon & Svensson, 2019).

Doucouliagos, Hennessy, and Mallick (2019) argue that infant mortality rates measure the most critical health outcome since it is a good measurement of how the rest of society is functioning. Further, the measure is strongly affected by variations in economic conditions, which has a distinct impact on other health outcomes, such as expected lifetime. A meta-analysis review of

47 econometric studies by Gallet and Doucouliagos (2017) establishes that public spending on health reduces infant mortality, with an elasticity of -0.13. This means that increased health spending will improve the average health outcome. For an overview of the global changes in child mortality rates under 1800 to 2015, see figure 6 in appendix A.

Explanatory Variable: Corruption

There are various ways to measure corruption, and we are using three different measurements to test if the results are consistent independently of which measure being used. The most commonly used is CPI, available since 1995, and CCI, available since 1996. Both measures are based on perception from different sources, such as surveys, business experts, and risk ratings from private companies. CPI measures the perceived corruption in the public sector and ranges from 0 to 100, where 0 indicates high corruption and 100 means very clean. The index was first developed in 1995 but the methodology used to construct the index was revised by TI in 2012 to ensure that the scores could be compared between the years thereafter. The latest available CPI for 2018 is based on 13 surveys and experts' judgments on 180 countries. Due to a change in methodology, the index is a bit problematic while comparing with estimates before and after 2012 (TI, 2018c). This further motivates why it will only be used as a robustness check instead of having it as the variable of interest.

CCI origins from WGI and comprises one of the six dimensions of governance that are individually estimated. The other five dimensions are voice and accountability, political stability, and absence of violence, government effectiveness, regulatory quality, and the rule of law. The WGI reports aggregate and individual governance indicators for over 200 countries and territories. The aggregate indicators are based on over 30 individual data sources produced by a variety of NGOs, think tanks, international organizations, etcetera. The methodology for the indicator is developed by Kaufmann and Kraay, for the World Bank. CCI measures the perception of the extent to which public power is exercised for private gain. The index ranges from -2.5 to 2.5, where the negative value indicates high corruption, and positive values the opposite (The World Bank, 2019c).

There may be some additional problems with these two measures. Researchers, such as Standaert (2015), and Hawken and Munck (2011), point out that these measures can be unsuitable for longitudinal analyses. The fact that the methodology has changed for CPI may

also affect the variables driving the changes in corruption levels. Due to the lack of a wide range of alternatives for measuring corruption, CPI and CCI have broadly been accepted as endurable indicators.

Another somewhat new measure is BCI, which is developed by the Study Hive for Economic Research and Public Policy Analysis at Ghent University. BCI aims to correct the problems that other measures have by using a state-space model. The methodology for the indicator relies on a Bayesian Gibbs sampling algorithm, and it corrects for missing values. This allows the indicator to be estimated without manipulations or assumptions. Some researchers suggest that it is a more reliable measurement over time than CCI and CPI, which is why BCI is chosen to be the primary indicator for this paper. The BCI ranges between 0 and 100, but unlike CPI, an increased score implies a higher level of perceived corruption (Standaert, 2015).

3.3.3 Description of Databases

The compiled data in the study is collected from several different sources. The primary data source is the QoG Standard Dataset, put together by the QoG Institute (Teorell et al. 2019). The institute is an independent research institute founded by Professor Rothstein and Professor Holmberg within the Department of Political Science at the University of Gothenburg. The questions addressed by the QoG Institute are how to create and preserve high-quality government institutions and how the quality may influence the socio-economic condition. The dataset established by the QoG Institute is one of the most complete datasets within this field of research and compile data from different reliable and famous sources such as OECD, World Bank, and UN (QoG, 2018). The four health indicators, measures of fractionalization, urbanization, GDP per capita, and the BCI are all drawn from this dataset. Data over mean age of women at childbirth as well as data of health expenditure are drawn from the OECD database.

The two other corruption indicators, CPI and CCI, are collected from TI and the WGI hosted by the World Bank. TI is an organization striving for a world free from corruption (TI, 2018d) and is the leading global indicator of corruption in the public sector. The index is based on surveys that are presented annually and provides a snapshot of the relative level of corruption in 180 countries (TI, 2018b). The WGI has been reported since 1996, for over 200 states. The data summarizes information from about 30 other data sources, mainly surveys, from private households, commercial businesses, non-governmental organizations, and the public sector (The World Bank, 2019c).

4 Results

This section will present the results of the study. The first part of this section provides the empirical results where the effect of corruption is measured with BCI. The second part consists of the results from the robustness checks. The third part will summarize the findings.

4.1 Empirical Results

First off, there is a need to test the data, to be able to perform the models. Initially, we test the data for multicollinearity, i.e., whether or not there exists a high internal correlation between the explanatory variables. The test for multicollinearity reports no worrisome results in any of the tests (the estimates of VIF are lower than 10), such that we can continue using all the variables of interest together with the control variables chosen for the study. Further, the data has to be tested for the possible existence of a heteroscedasticity problem with the variance. When conducting the heterogeneity test, there is indeed no constant variance, and the data is heteroscedastic. To correct for this, one should use robust standard errors to deal with the heteroscedasticity problem.

After conducting the tests, the regressions can be run. The results are compiled into table 2, containing each of the four measures of health outcomes. Model (1) in table 2, are the results from the bivariate relation using OLS without any control variables (also known as the first restricted model), while models (2) is the bivariate fixed effects model (also referred to as the second restricted model). Model (3) to (5) are two-way fixed effects models (also referred to as the general model), including control variables and the time- and country-specific effects. As described in section 3.1, the control variables are added in a specific order, where the social-, infrastructural-, and economic- factors are added as clusters of controls, respectively. Since the variable of interest is corruption, the coefficients of the control variables are excluded from the table.

	(1) OLS	(2) FE	(3) FE	(4) FE	(5) FE
		Dependent	variable: infant	mortality	
DCI	0.176**	0.202*	0.059*	0.059*	0.052*
BCI	(0.078)	(0.109)	(0.030)	(0.030)	(0.028)
R-squared	0.045	0.045	0.795	0.796	0.793
No. of observations	824	824	714	714	695
		Dependent v	ariable: neonata	l mortality	
DCI	0.095**	0.111	0.023	0.023	0.025
BCI	(0.046)	(0.067)	(0.024)	(0.024)	(0.025)
R-squared	0.035	0.035	0.733	0.733	0.717
No. of observations	824	824	714	714	695
		Dependent	variable: child	mortality	
	0.216**	0.256*	0.077**	0.077**	0.068**
BCI	(0.095)	(0.135)	(0.036)	(0.036)	(0.032)
R-squared	0.045	0.045	0.798	0.798	0.798
No. of observations	824	824	714	714	695
		Dependent	variable: life ex	spectancy	
DCI	-0.153***	-0.181**	-0.023	-0.023	-0.026
BCI	(0.049)	(0.087)	(0.028)	(0.028)	(0.027)
R-squared	0.064	0.064	0.932	0.933	0.937
No. of observations	788	788	714	714	695
Year dummy	No	No	Yes	Yes	Yes

Table 2: The effect of corruption on different health outcomes, with OLS and fixed effects models

Note: There are 36 countries. Number in parenthesis are robust standard errors clustered by country. Significance level: *** 1% ** 5% *10%

Model (3) to (5) are two-way FE. Added clusters of control variables in:

⁻ model (3) are the social factors; mean age of mother at childbirth, ethnical-, linguistic-, and religious fractionalization.

⁻ model (4) is also the infrastructural factor; urbanization.

⁻ model (5) are also the economic factors; GDP/capita, total health expenditure as a share of GDP, and governmental health expenditure as a share of GDP.

As seen in table 2, when infant mortality is the dependent variable, i.e., when a child dies within the first year of life, the result from model (1) shows that the effect of corruption on the health outcome is rather high. When BCI increases with one unit, i.e., when a country gets more corrupt, then infant mortality increases with 17.6 infants per 100 000 live births, significant at a 5 percent level. However, changing from OLS to a fixed effects model in model (2) the coefficient increases slightly to 20.2 infants per 100 000 live births. When adding the time-specific effect together with the social factors, the coefficient drops significantly, to 5.9 infants per 100 000 live births. In addition to the drop in the coefficient, one can see a somewhat large drop in the number of observations due to omitted control variables (from 824 to 714 observations). When adding the infrastructural and economic factors, the coefficient decreases slightly further, to 5.2 infants per 100 000 live births, together with a decrease in the number of observations in the final model. All coefficients estimated with fixed effects are significant at a 10 percent level.

For neonatal mortality, i.e., when the infant dies within the first 28 days after birth, the bivariate relation using OLS with BCI is not as high as for infant mortality, but still substantial on 9.5 per 100 000 live births when BCI increases with one unit. However, the coefficient is only significant for model (1), whereas the residual models, i.e., all the models using fixed effects, do not show any acceptable levels of significance.

When using child mortality as the dependent variable, i.e., children who die within the first five years of life, the magnitude of the coefficient is somewhat larger than for infants in all models. However, the trend of how it changes when the clusters of social, infrastructural, and economic factors are added is similar. The bivariate relation of an OLS estimation with BCI is 21.6 children per 100 000 live births when corruption increases with one unit. The coefficient increases slightly when changing to a fixed effects model but decreases instantly when adding the social factors and the time dummy. When all three clusters of control variables are included, the effect has fallen to 6.8 children per 100 000 live births, significant at a 5 % level.

The last health outcome presented in table 2 is life expectancy at birth. Using OLS, the bivariate relation with corruption, i.e., model (1), display that when there is a one unit rise in corruption, the expected lifetime will decrease with 0.153 years, whereas the fixed effect bivariate relation is somewhat more substantial, a decrease of 0.181 years. Model (1) is significant at a 1 percent level, while the fixed effect is significant at a 5 percent level. However, when adding the control variables and the time dummy, the coefficient decreases to 0.026 years and loses significance.

The number of observations in the regressions decreases when adding the control variables, from 824 to 695 for mortality rates, and from 788 to 695 for life expectancy. This should not be problematic since the panel dataset is strongly balanced. However, to be certain that the results are not affected by the number of observations in the sample, a re-estimation of the first model for OLS and the fixed effect is conducted, only including 695 observations (see table 4 in appendix B). The bivariate relationship between health outcomes and corruption decreases somewhat and is, to some extent, affected by the number of observations. When continuing with adding control variables, and still keeping the number of observations constant at 695, the drop in the estimated coefficients when including the social factors are still quite large. However, when re-estimating the models including both social and infrastructural factors, the difference is negligible to the results in table 2. This may be due to the small difference in the number of observations, from 714 to 695.

4.2 Robustness Check

In the first part of the robustness check, the aim is to control how robust the results are by using corruption indices produced by other institutions. For each of the dependent variables, we have controlled the results for CPI and CCI by performing the same procedure as with BCI, i.e., successively adding clusters of the social-, infrastructural-, and economic factors respectively. In the second part of the robustness check, the results of the IV/2SLS approach will be presented.

4.2.1 Testing the Models with Two Other Corruption Indices

	(1) OLS	(2) FE	(1) OLS	(2) FE
-	Dependen	t variable:	Depender	it variable:
	infant m	nortality	neonatal mortality	
	0.044*	0.052*	0.018	0.025
BCI	(0.025)	(0.032)	(0.018)	(0.025)
R-squared	0.783	0.793	0.703	0.717
No. of observations	695	695	695	695
СЫ	-0.013*	-0.021**	-0.008	-0.014*
ULI	(0.010)	(0.010)	(0.007)	(0.007)
R-squared	0.786	0.793	0.713	0.727
No. of observations	688	688	688	688
	0.024	0.024	0.015	0.016
CCI	0.024	0.024	0.015	0.016
D	(0.017)	(0.019)	(0.010)	(0.011)
K-squared	0.754	0.761	0.689	0.697
	589	569	569	569
-	Danandan	t voriable.	Donondon	t vomoble.
-	Dependen child m	t variable:	Depender	t variable:
	Dependen child m	t variable: ortality	Depender life exp	nt variable: bectancy
	Dependen child m 0.056**	t variable: ortality 0.068**	Depender life exp -0.017	ut variable: bectancy -0.026
BCI	Dependen child m 0.056** (0.028)	t variable: ortality 0.068** (0.032)	Depender life exp -0.017 (0.024)	t variable: bectancy -0.026 (0.027)
BCI R-squared	Dependen child m 0.056** (0.028) 0.788	t variable: ortality 0.068** (0.032) 0.798	Depender life exp -0.017 (0.024) 0.900	-0.026 (0.027) 0.937
BCI R-squared No. of observations	Dependen child m 0.056** (0.028) 0.788 695	t variable: ortality 0.068** (0.032) 0.798 695	Depender life exp -0.017 (0.024) 0.900 695	-0.026 (0.027) 0.937 695
BCI R-squared No. of observations	Dependen child m 0.056** (0.028) 0.788 695	t variable: ortality 0.068** (0.032) 0.798 695	Depender life exp -0.017 (0.024) 0.900 695	-0.026 (0.027) 0.937 695
BCI R-squared No. of observations	Dependen child m 0.056** (0.028) 0.788 695 -0.016*	t variable: ortality 0.068** (0.032) 0.798 695 -0.027**	Depender life exp -0.017 (0.024) 0.900 695 0.010	-0.026 (0.027) 0.937 695 0.009
BCI R-squared No. of observations CPI	Dependen child m 0.056** (0.028) 0.788 695 -0.016* (0.013)	t variable: ortality 0.068** (0.032) 0.798 695 -0.027** (0.013)	Depender life exp -0.017 (0.024) 0.900 695 0.010 (0.008)	-0.026 (0.027) 0.937 695 0.009 (0.007)
BCI R-squared No. of observations CPI R-squared	Dependen child m 0.056** (0.028) 0.788 695 -0.016* (0.013) 0.786	t variable: ortality 0.068** (0.032) 0.798 695 -0.027** (0.013) 0.796 (88)	Depender life exp -0.017 (0.024) 0.900 695 0.010 (0.008) 0.900	-0.026 (0.027) 0.937 695 0.009 (0.007) 0.936
BCI R-squared No. of observations CPI R-squared No. of observations	Dependen child m 0.056** (0.028) 0.788 695 -0.016* (0.013) 0.786 688	t variable: ortality 0.068** (0.032) 0.798 695 -0.027** (0.013) 0.796 688	Depender life exp -0.017 (0.024) 0.900 695 0.010 (0.008) 0.900 688	-0.026 (0.027) 0.937 695 0.009 (0.007) 0.936 688
BCI R-squared No. of observations CPI R-squared No. of observations	Dependen child m 0.056** (0.028) 0.788 695 -0.016* (0.013) 0.786 688 0.023	t variable: ortality 0.068** (0.032) 0.798 695 -0.027** (0.013) 0.796 688 0.021	Depender life exp -0.017 (0.024) 0.900 695 0.010 (0.008) 0.900 688 -0.019	-0.026 (0.027) 0.937 695 0.009 (0.007) 0.936 688
BCI R-squared No. of observations CPI R-squared No. of observations CCI	Dependen child m 0.056** (0.028) 0.788 695 -0.016* (0.013) 0.786 688 0.023 (0.021)	t variable: ortality 0.068** (0.032) 0.798 695 -0.027** (0.013) 0.796 688 0.021 (0.024)	Depender life exp -0.017 (0.024) 0.900 695 0.010 (0.008) 0.900 688 -0.019 (0.014)	$\begin{array}{c} -0.026 \\ (0.027) \\ 0.937 \\ 695 \\ \hline 0.009 \\ (0.007) \\ 0.936 \\ 688 \\ \hline 0.010 \\ (0.012) \\ \end{array}$
BCI R-squared No. of observations CPI R-squared No. of observations CCI R-squared	Dependen child m 0.056** (0.028) 0.788 695 -0.016* (0.013) 0.786 688 0.023 (0.021) 0.755	t variable: ortality 0.068** (0.032) 0.798 695 -0.027** (0.013) 0.796 688 0.021 (0.024) 0.762	Depender life exp -0.017 (0.024) 0.900 695 0.010 (0.008) 0.900 688 -0.019 (0.014) 0.891	-0.026 (0.027) 0.937 695 0.009 (0.007) 0.936 688 0.010 (0.012) 0.929
BCI R-squared No. of observations CPI R-squared No. of observations CCI R-squared No. of observations	Dependen child m 0.056** (0.028) 0.788 695 -0.016* (0.013) 0.786 688 0.023 (0.021) 0.755 589	t variable: ortality 0.068** (0.032) 0.798 695 -0.027** (0.013) 0.796 688 0.021 (0.024) 0.762 589	Depender life exp -0.017 (0.024) 0.900 695 0.010 (0.008) 0.900 688 -0.019 (0.014) 0.891 589	-0.026 (0.027) 0.937 695 0.009 (0.007) 0.936 688 0.010 (0.012) 0.929 589

Table 3: Re-estimating the models for CPI and CCI

Note: There are 36 countries. Number in parenthesis are robust standard errors clustered by country. Significance level: *** 1% ** 5% *10%.

Model (2) is a two-way FE. Added clusters of control variables for both model (1) and (2) are:

- the social factors, i.e., mean age of mother at childbirth, ethnical-, linguistic-, and religious

fractionalization;

- the infrastructural factor, i.e., urbanization;

- the economic factors, i.e., GDP/capita, total health expenditure as a share of GDP, and governmental health expenditure as share of GDP.

We are interested in investigating whether the results of the models, including all control variables, are robust or not. Therefore, additional tests are performed where BCI is exchanged with two other corruption indices (CPI and CCI). For comparability reasons, the two other corruption measures will be conducted with both an OLS and a two-way fixed effects model. The results are presented in table 3 where model (1) refers to the estimated effect on each health outcome using an OLS, including all control variables. Model (2) is identical to model (1), with the distinction of including a year dummy, being a two-way fixed effects model.

When using infant- and child mortality rates as the dependent variables, the study finds that the coefficients for corruption measured with CPI are significantly smaller in comparison to BCI. However, the estimated coefficients behave in the same way, i.e., when corruption decreases with one unit, the infant- and child mortality rates decrease (note that the CPI is read oppositely to BCI). The third measure of corruption, CCI, does not behave as BCI or CPI. The effects on these mortality rates are minimal, and positive, implying that when corruption decreases in a country, the mortality rates should increase (note that CCI is also read oppositely to BCI). Further, the estimated coefficients of CPI behave in the same direction as BCI for the two additional health outcomes. However, CCI again reverses its direction, with the only exception in the case of fixed effects on life expectancy, but there are close to no sign of significance for neonatal mortality or life expectancy.

In conclusion, CPI affirms the results of BCI by the direction of the signs and level of significance. One can also see that the magnitude of CPI is smaller than what BCI estimates the effect to be. CCI, however, does not provide the same results as BCI nor CPI, with the only exception of life expectancy. It also changes signs, from negative to positive, however insignificant in all cases. When controlling for the correlation between the corruption measures, the study finds that there indeed exists a strong correlation between BCI and CPI while no correlation between BCI and CCI is found. Although the scale for which CCI is measured differs from BCI and CPI, naturally implying that the effect should not be similar, at least the direction of the effect should correspond if the choice of the measure were inessential. Yet, the findings suggest that it does indeed matter which measurement or indices of corruption one use when doing quantitative research on the effect of corruption.

4.2.2 IV/2SLS Approach

It is difficult to say with certainty if there exists an endogeneity problem. It is not unlikely that corruption may be correlated with the error term, such that the OLS is biased. If the correlation is not coetaneous, then the OLS or two-way fixed effects methods can still be consistent, such that the efficient model in this paper, is indeed the general equation (1). Some papers in existing literature discuss this potential endogeneity problem but cannot confirm the problem. That is why we tackle this by an IV/2SLS approach as a part of the robustness check. The results are presented in table 5 to 8 (see appendix C). Model (1) in each table presents when the two- and three periods lagged BCI are applied as instruments for current BCI. When comparing the estimated coefficients from using a fixed effects model with the 2SLS approach, the results are, to a large extent, very similar, both in the case of infant mortality and child mortality. However, the test for endogeneity fails, which indicates that BCI is exogenous such that there are no apparent signs of an endogeneity problem.

Further, it passes the other tests with satisfactory results, meaning there is no under- or overidentification, and the instruments are not weak. Thus, since the results of fixed effects and 2SLS when using lagged BCI two- and three periods are almost identical, the robustness check confirms that the main results, to a large extent, indeed are valid. However, one should entrust the results from the fixed effects rather than the IV results, since the empirical method using fixed effects is more efficient.

Model (2) in each table presents the results when using the democracy score and fuel export as instruments for BCI. The results are somewhat mixed, proposing that there is an endogeneity problem when estimating the effects for child- and infant mortality, whereas a non-existing problem for neonatal mortality and life expectancy. Still, the instruments fail the test for each dependent variable, implying that the instruments are invalid and/or weak. This might be due to the values of the instrumental variables. Democracy score is rather high for the sample, where the mean is 9.46 out of 10, where 10 is best. This means that the sample is rather democratic compared to if the sample would have included all countries in the world, where there is a more substantial variation. The mean of the fuel export is also just about 7.59 percent, i.e., rather low. Countries in the sample are not big exporters of fuel, which theoretically would mean that there is less corruption. The coefficient of BCI is also significantly higher than the OLS and fixed effects models but is not at an acceptable significance level. This suggests that using democracy score and fuel export as instruments do not solve a potential endogeneity problem, such that

one cannot with certainty say that there is an endogeneity problem, or that the instruments will solve this potential endogeneity problem.

4.3 Key Findings

The key findings in this paper are that, when both excluding and including controls, BCI has a significantly positive effect on infant mortality, and child mortality rates. This means that when a country becomes more corrupt, infant and child mortality rates increase. The estimated effects slightly increase when changing method from OLS to a fixed effects model but decrease again when more factors are added to the regression, remaining significant throughout all models. The coefficients of corruption on neonatal mortality are also positive, but insignificant in all cases, except for model (1). The coefficients of BCI on life expectancy are negative, indicating that life expectancy decreases when corruption increases. Nevertheless, only the coefficients for the bivariate relation tend to show acceptable significance levels, both in the case of OLS and fixed effects.

To conclude the key findings of the empirical results, one can see that the infant mortality rate and child mortality rate behave in the same way. Using a two-way fixed effects model, including all control variables imply that a one unit change in corruption measured with BCI is associated with a change in infant mortality rates with 5.2 children (per 100 000 live births). The effect is somewhat similar for child mortality, namely 6.8 children (per 100 000 live births). For neonatal mortality and life expectancy, the results in most cases are insignificant, although the direction of the effects goes in line with previous findings of the existing literature. Hence, one should be somewhat careful when concluding the effects of corruption on neonatal mortality and life expectancy in the member states of OECD. To summarize, corruption tends to affect health outcomes in OECD countries negatively, although the effect is not as widespread among the different health outcomes as previously found when looking at the effect globally.

5 Discussion

In this section, we discuss the findings and the possible explanations to why the results in this paper differ from previous research. The first part of the discussion will focus on the empirical results from the main analysis, while the second part will focus on the robustness checks. Finally, we will conclude with a contribution to the existing literature by going beyond why corruption exists in the healthcare sector and rather discuss how corruption causes death.

Empirical Results of the Main Analysis

From investigating the effects on corruption on health outcomes, we can confirm that corruption indeed costs lives in OECD countries and that a reduction of corruption should have a positive impact on health outcomes. In contrast to previous studies, the magnitude of the effect tends to vary substantially, and the suggested reasons for this may be several. First, only using the 36 member states of OECD as countries of interest implies a considerably smaller sample compared to previous studies, that in contrast include more countries. It is not unreasonable to assume that the sample size could be a major cause of this difference. Secondly, only including OECD countries in the study implies that countries with very high mortality rates and low levels of life expectancy are removed from the sample, reducing the effects significantly by excluding countries with substantially higher mortality rates and shorter expected lifetime. This includes countries such as Somalia, Chad and the Central African Republic with child mortality rates above 120 (per 1 000 live births) in 2017 (World Bank, 2019d) and Sierra Leone, the Central African Republic and Chad with expected lifetime slightly above 50 years in 2017 (World Bank, 2019b). Thirdly, during the time period 1995 - 2017 the variation among the mortalityand life expectancy rates was fairly low. This weakness applies to both our study and on other research since our time period is the largest up to date. It is arguably to assume that the study would need to include a time period of at least 30-40 years, to be able to account for the changes in mortality rates and life expectancy.

An additional suggestion of why the magnitude of the effects in this paper tends to be substantially lower compared to previous studies might be the introduction of mean age of mothers at childbirth as a control variable. From the regressions we have found that mothers age at childbirth absorbs a large part of the effect on health outcomes, decreasing the effects from corruption (see the difference between model (2) and (3)). From excluding this variable, keeping it unobserved, a large part of the effect that otherwise would have been assigned to it may instead be assigned to corruption. This suggests that other studies get unreasonably high effects from failing to include an important variable. However, it is hard to state that the effect of other studies would change from adding mothers' age as a control variable without having performed the test even though the likelihood of finding a changed magnitude on the effect of corruption on health outcomes seems relatively large. This could be an interesting way to develop the research further; to investigate how the effect of corruption on health outcomes changes from adding this as a control variable, when including more countries than only the 36 member states of OECD.

Based on previous literature, the level of education of mothers at childbirth is an important factor for mortality rates. Some papers use primary and secondary school enrolment as measures of education. However, these are not interesting to control for in this study since almost everyone goes through these education entities in OECD countries, such that the control variable would be omitted when applying fixed effects model, because the observations would remain constant over time.

Instead, using mothers' age at childbirth as an alternative to educational attainment can at least catch some of the effects that education has. Heck, Schoendorf, Ventura and Kiely (1997) find that mothers with educational attainment postpone their first childbirth. That is, due to more years of education, women have children at an older age. This generates positive outcomes such as higher income levels and better household wealth, meaning women can care for the child in another sense, including the ability to pay for more healthcare if needed. Besides, Mills, Rindfuss, McDonald and te Velde (2011) find clear empirical evidence that there is a general postponement of childbirth, to some extent, explained by the increasing level of women's education and as such catch some of the effects.

As presented in previous sections, the effect of corruption on neonatal mortality rates is insignificant in OECD countries, although other studies have found an effect globally. We cannot say for sure why the effect completely disappears in our study, but we believe it may depend on OECD countries offering high quality premature- and obstetric care compared to many emerging countries not belonging to OECD. In contrast to neonatal care, infant and child care include a more extended period of life (compare 28 days to up to 5 years) which thus make

it harder to maintain a high quality for all countries, even for OECD countries, since it includes a wider range of patients. Hence, this could explain why corruption significantly increases infant- and child mortality rates in the sample.

Robustness Check

The robustness analysis showed that the usage of CPI and BCI generate results that move in the same direction. However, there is a difference in the magnitude of the estimated coefficients. Using BCI as a measure of corruption provides estimations that are more than twice as large as the estimation with CPI. One possible explanation could be that CPI is perception-based; as such, it corresponds to people's ability to observe or experience corruption. In previous literature, the ability to see corruption is stated to be difficult, such that there might be underestimation with the measurement. The robustness analysis also implicates that the third corruption measurement, CCI, does not behave in the same way as BCI or CPI. Accordingly, there is indeed a difference in quantitative research with the choice of measurement of corruption and how it affects the results. This finding contradicts other results, such as in the paper by Li et al., (2018), and Factor and Kang (2015). If this contradiction depends on the sample, time period, or that perception-based indices underestimates the real effect, is a potential subject for additional research within this field of study.

Furthermore, the results from the second part of the robustness check evaluate whether one should use an IV approach. The results show that there is not an endogeneity problem when using the corruption measure with two and three periods lagged BCI and that the chosen instruments are functioning. Li et al. (2018) argue that lagged corruption is a suitable instrument for current corruption. Also, using a lagged variable as an instrument is quite common in time series and sometimes suitable for panel data. There might, though, be a potential problem with the fulfillment of the second condition, that lagged corruption rates are exogenous to the selected health outcomes. Arguing that the level of corruption two years back should not affect today's mortality rates seems somewhat strange. In the case of losing a more substantial amount of money from the budget due to corruption one year, the healthcare two years later should most likely still be affected as a result of delays in the system. Hence, it can be argued that mortality rates and life expectancy could be affected by corruption two periods back.

Moreover, using the democracy score and fuel export as instruments for corruption does provide reasoning for an endogeneity problem. However, the tests for the validity of the instruments fail, such that it is difficult to argue whether or not there is an endogeneity problem using the paper's sample for OECD countries. The reasoning that Lio and Lee (2016) have for using these two as instruments is legitimate, however, it might not be suitable to model on OECD countries since the level of democracy is high for all countries while the fuel export is quite low. Thus, it might not give the same impact on corruption as it could with another sample.

Why does Corruption Kill?

Most literature investigating corruption in the healthcare sector highlights the problems of corruption and provides detailed explanations of how corruption is embedded in the sector, such as bribes, higher fees for patients, and prescriptions of unnecessary or unclean drugs. It is somewhat established that the poorest people in society suffer the hardest from corruption in the healthcare sector. Findings from Mexico indicate that the typical family among the poorest pay close to one-third of their income to bribes (TI, 2018e). Having to pay a bribe to healthcare professionals to receive medical care may mean that a family cannot provide their children the care needed, in turn implying that a child dies because of financial problems. A different turnout of having to pay bribes to civil servants could be that the family has no money left for food, causing undernutrition, which as well may lead to deaths. Additional causes of death are the sale of fake and adulterated medications or the usage of re-packed equipment or drugs with expired dates. Further, with money disappearing from health budgets, already scarce resources become even scarcer, limiting patients to receive the proper care needed, which in turn also may result in scenarios of deaths. These examples are just a few of the various causes of death resulting from corruption, illustrating the importance of combat corruption in OECD countries as well as worldwide.

All in all, corruption is a global problem and a complex phenomenon affecting health levels negatively. Hence, it is of great importance that future research continues to investigate this subject to improve and better understand the mechanisms of how corruption kills. Further, the research should also aim to develop ways of reducing corruption levels such that health outcomes globally improve and fewer people are hurt from it.

6 Conclusion

This paper aimed to estimate the effect of corruption on four major health outcomes, using cross-country panel data, including the 36 member states of OECD for the period of 1995 – 2017. Further, we aimed to investigate if the choice of corruption index matters for the results, which previous studies reject. The main corruption indicator used in this study is BCI, yet two additional corruption measures are included to check the robustness of the results, namely CPI and CCI. The health indicators are infant-, neonatal-, child mortality rates, and life expectancy; indicators that are frequently used in the existing literature. Throughout the study, we use OLS, fixed effects models, and a 2SLS method to estimate the effects of corruption on health outcomes by adding clusters of control variables categorized into social, infrastructural, and economic factors.

The first contribution of the paper is that we indeed found that corruption affects health, although the effect is not as widespread among the four health outcomes as previously found. We found that increased levels of corruption significantly increase infant- and child mortality rates across the member states of OECD, but close to no such significant results are found for neonatal mortality rates and life expectancy. A second contribution is that the results are found by using the relatively new and unexplored corruption index, BCI, which has not been used in previous literature. A third contribution is that we find that using different corruption indices indeed generates different results, contradicting previous literature.

In conclusion, by further investigating the effects of corruption on health outcomes, the importance of reducing corruption to improve the general public health level is once again proved. Corruption is a complex phenomenon without any clear-cut ways of how to reduce it, although different scholars have various suggestions. Nonetheless, there are no quick-fixes to tackle corruption, as confirmed by Larry Diamond in his short piece on democracy:

Endemic corruption is not some flaw that can be corrected with a technical fix or a political push. It is the way that the system works, and it is deeply embedded in the norms and expectations of political and social life. Reducing it to less destructive levels - and keeping it there - requires revolutionary change in institutions (Carothers, Elshtain, Diamond, Ibrahim & Bangura, 2007, p.119).

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Appendix A



Figure 4: OECD countries as of July 5th, 2018

Europe	North America	Asia	Oceania	South America
Austria	Canada	Japan	Australia	Chile
Belgium	Mexico	South Korea	New Zealand	
Czech Republic	United States	Turkey		
Denmark		2		
Estonia				
Finland				
France				
Germany				
Greece				
Hungary				
Iceland				
Ireland				
Israel				
Italy				
Latvia				
Lithuania				
Luxembourg				
Netherlands				
Norway				
Poland				
Portugal				
Slovakia				
Slovenia				
Spain				
Sweden				
Switzerland				
United Kingdom				

List of the 36 member states of OECD



Figure 5: Relation between CPI and health outcomes



Figure 6: Child mortality rates across the world 1800, 1950, 2000 and 2015

The figure illustrates the historical rates of child mortality, i.e., under-five year mortality, from 1800 to 2015. There has been a substantial decrease from 1950 until today, where only the last 15 years a vast improvement in preventing child mortality has occurred, especially in Sub-Saharan Africa. Maps extracted from Roser (2019).

Appendix B

Tuete T: The estimating B er jor (
	(1)	(2)
	OLS	FE
	Dependent variabl	e: infant mortality
PCI	0.115**	0.126*
BCI	(0.049)	(0.069)
R-squared	0.060	0.060
	Dependent variable	: neonatal mortality
PCI	0.058*	0.065
BCI	(0.030)	(0.046)
R-squared	0.040	0.040
	Dependent variab	le: child mortality
RCI	0.140**	0.156*
BCI	(0.057)	(0.082)
R-squared	0.064	0.064
	Dependent variab	le: life expectancy
RCI	-0.130***	-0.149
bei	(0.048)	(0.092)
R-squared	0.049	0.049
No. of observations	695	695
Year dummy	No	No

Table 4: Re-estimating BCI for 695 observations

Note: There are 36 countries. Number in parenthesis are robust standard errors clustered by country. Significance level: *** 1% ** 5% *10%

Appendix C

	Dependent variable: infant mortality						
	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	
BCI	0.040*** (0.011)	0.251** (0.114)					
Centered R-squared	0.954	0.911					
No. of observations	625	646					
СРІ			-0.041** (0.010)	0.150 (0.224)			
Centered R-squared			0.958	0.850			
No. of observations			607	642			
ССІ					-0.004 (0.024)	-0.342 (0.296)	
Centered R-squared					0.969	0.758	
No. of observations					409	549	
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	
Test of endogeneity	Chi-sq(1) = 2.016	Chi-sq(1) = 6.282**	Chi-sq(1) = 0.888	Chi-sq(1) = 1.135	Chi-sq(1) = 1.752	Chi-sq(1) = 9.645***	
Underidentification test	Chi-sq(2) = 138.95***	Chi-sq(2) = 9.60***	Chi-sq(2) = 58.3***	Chi-sq(2) = 1.565	Chi-sq(2) = 40.4***	Chi-sq(2) = 1.781	
Overidentification test	Chi-sq(1) = 1.888	Chi-sq(1) = 9.223***	Chi-sq(1) = 10.49***	Chi-sq(1) = 6.02**	Chi-sq(1) = 3.074*	Chi-sq(1) = 1.626	
Weak instrument test	(i) 921.56 (ii) 528.21	(i) 4.402 (ii) 5.180	(i) 137.85 [•] (ii) 101.04 [•]	(i) 0.534 (ii) 0.552	(i) 58.137 (ii) 39.721	(i) 1.183 (ii) 0.919	

 Table 5: Robustness result using IV approach for infant mortality

Note: There are 36 countries. Number in parenthesis are robust standard errors. Significance level, ***10 (*10%)

Significance level: *** 1% ** 5% *10%

Instrumental variables for model (1): BCI_lag2 and BCI_lag3, (3): CPI_lag2 and CPI_lag3, (5): CCI_lag2 and CCI_lag3

Instrumental variables for models (2), (4) and (6): democracy score and fuel export (percent of merchandise export)

Test of endogeneity: The null hypothesis is that "variables are exogenous"

Underidentification test: Kleibergen-Paap rk LM statistic

Overidentification test: Hansen J statistic. The null hypothesis is that "instruments are valid"

Weak instrument test: (i) Cragg-Donald Wald F statistic (ii) Kleibergen-Paap rk Wald F statistic

	Dependent variable: neonatal mortality						
	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	
BCI	0.017** (0.008)	0.121 (0.079)					
Centered R-squared	0.937	0.887					
No. of observations	625	646					
СРІ			-0.024***	0.084			
Centered R-squared			0.944	0.824			
No. of observations			607	642			
ССІ					-0.002 (0.015)	-0.146 (0.147)	
Centered R-squared					0.962	0.813	
No. of observations					409	549	
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	
Test of endogeneity	Chi-sq(1) = 1.644	Chi-sq(1) = 2.252	Chi-sq(1) =0.279	Chi-sq(1) = 1.525	Chi-sq(1) = 0.232	Chi-sq(1) = 3.959**	
Underidentification test	Chi-sq(2) = 136.9***	Chi-sq(2) = 9.60***	Chi-sq(2) = 58.3***	Chi-sq(2) = 1.565	Chi-sq(2) = 40.4***	Chi-sq(2) = 1.781	
Overidentification test	Chi-sq(1) = 0.662	Chi-sq(1) = 4.723**	Chi-sq(1) = 7.405***	Chi-sq(1) = 2.87*	Chi-sq(1) = 3.303*	Chi-sq(1) = 1.420	
Weak instrument test	(i) 921.56 (ii) 528.21	(i) 4.402 (ii) 5.180	(i) 137.85 [•] (ii) 101.04 [•]	(i) 0.534 (ii) 0.552	(i) 58.137 (ii) 39.721	(i) 1.183 (ii) 0.919	

Tahle	6:	Robustness	result	using	IV	approach	for	neonatal	mortality	,
10000	••	100000000000000	1 050000	"Sung		approach.	,0,	110011011011		e

Note: There are 36 countries. Number in parenthesis are robust standard errors.

Significance level: *** 1% ** 5% *10%

Instrumental variables for model (1): BCI_lag2 and BCI_lag3, (3): CPI_lag2 and CPI_lag3, (5): CCI_lag2 and CCI_lag3

Instrumental variables for models (2), (4) and (6): democracy score and fuel export (percent of merchandise export)

Test of endogeneity: The null hypothesis is that "variables are exogenous"

Underidentification test: Kleibergen-Paap rk LM statistic

Overidentification test: Hansen J statistic. The null hypothesis is that "instruments are valid"

Weak instrument test: (i) Cragg-Donald Wald F statistic (ii) Kleibergen-Paap rk Wald F statistic

	Dependent variable: child mortality						
	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	
BCI	0.052*** (0.013)	0.309** (0.135)					
Centered R-squared	0.951	0.905					
No. of observations	625	646					
СРІ			-0.050^{***}	0.212			
Centered R-squared			0.955	0.804			
No. of observations			607	642			
ССІ					-0.007 (0.0289)	-0.433 (0.362)	
Centered R-squared					0.967	0.728	
No. of observations					409	549	
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	
Test of endogeneity	Chi-sq(1) = 1.968	Chi-sq(1) = 5.943**	Chi-sq(1) = 0.951	Chi-sq(1) = 2.647	Chi-sq(1) = 1.578	Chi-sq(1) = 10.59***	
Underidentification test	Chi-sq(2) = 138.95***	Chi-sq(2) = 9.60***	Chi-sq(2) = 58.3***	Chi-sq(2) = 1.565	Chi-sq(2) = 40.4***	Chi-sq(2) = 1.781	
Overidentification test	Chi-sq(1) = 1.363	Chi-sq(1) = 12.48***	Chi-sq(1) = 11.90***	Chi-sq(1) = 5.679**	Chi-sq(1) = 3.244*	Chi-sq(1) = 1.751	
Weak instrument test	(i) 921.56 (ii) 528.21	(i) 4.402 (ii) 5.180	(i) 137.85 [•] (ii) 101.04 [•]	(i) 0.534 (ii) 0.552	(i) 58.137 (ii) 39.721	(i) 1.183 (ii) 0.919	

Table 7: Robustness	result using IV	approach	for	child	mortality
	()		/		~

Note: There are 36 countries. Number in parenthesis are robust standard errors.

Significance level: *** 1% ** 5% *10%

Instrumental variables for model (1): BCI_lag2 and BCI_lag3, (3): CPI_lag2 and CPI_lag3, (5): CCI_lag2 and CCI_lag3

Instrumental variables for models (2), (4) and (6): democracy score and fuel export (percent of merchandise export)

Test of endogeneity: The null hypothesis is that "variables are exogenous"

Underidentification test: Kleibergen-Paap rk LM statistic

Overidentification test: Hansen J statistic. The null hypothesis is that "instruments are valid"

Weak instrument test: (i) Cragg-Donald Wald F statistic (ii) Kleibergen-Paap rk Wald F statistic

	Dependent variable: life expectancy						
	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	
BCI	-0.021** (0.010)	-0.022 (0.064)					
Centered R-squared	0.984	0.984					
No. of observations	625	646					
СРІ			0.025*** (0.008)	-0.166 (0.190)			
Centered R-squared			0.983	0.925			
No. of observations			607	642			
ССІ					0.029** (0.013)	0.094 (0.093)	
Centered R-squared					0.989	0.979	
No. of observations					409	549	
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	
Test of endogeneity	Chi-sq(1) = 2.191	Chi-sq(1) = 0.002	Chi-sq(1) = 5.164**	Chi-sq(1) = 4.244**	Chi-sq(1) = 5.059**	Chi-sq(1) = 1.443	
Underidentification test	Chi-sq(2) = 138.9***	Chi-sq(2) = 9.60***	Chi-sq(2) = 58.3***	Chi-sq(2) = 1.565	Chi-sq(2) = 40.4***	Chi-sq(2) = 1.781	
Overidentification test	Chi-sq(1) = 2.210	Chi-sq(1) = 6.837***	Chi-sq(1) = 6.662***	Chi-sq(1) = 0.689	Chi-sq(1) = 3.158*	Chi-sq(1) = 4.516**	
Weak instrument test	(i) 921.556 (ii) 528.213	(i) 4.402 (ii) 5.180	(i) 137.85 [•] (ii) 101.04 [•]	(i) 0.534 (ii) 0.552	(i) 58.137 (ii) 39.721	(i) 1.183 (ii) 0.919	

Note: There are 36 countries. Number in parenthesis are robust standard errors.

Significance level: *** 1% ** 5% *10%

Instrumental variables for model (1): BCI_lag2 and BCI_lag3, (3): CPI_lag2 and CPI_lag3, (5): CCI_lag2 and CCI_lag3

Instrumental variables for models (2), (4) and (6): democracy score and fuel export (percent of merchandise export)

Test of endogeneity: The null hypothesis is that "variables are exogenous"

Underidentification test: Kleibergen-Paap rk LM statistic

Overidentification test: Hansen J statistic. The null hypothesis is that "instruments are valid"

Weak instrument test: (i) Cragg-Donald Wald F statistic (ii) Kleibergen-Paap rk Wald F statistic