

# **CEIS Tor Vergata**

RESEARCH PAPER SERIES

Vol. 15, Issue 9, No. 420 – December 2017

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# ARE PERCEPTIONS OF CORRUPTION MATCHING REALITY? THEORY AND EVIDENCE FROM MICRODATA

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July 2017

## Abstract

Some criticism has been raised on the actual capability of corruption perception-based indices to gauge the essence of concepts they aim to measure. One can argue that perceptions about corruption are not matching reality and could be the reflection of distorted truth. Based on this evidence we provide a theoretical ground for the corruption decision-making process (objective corruption) and the corruption perception-making process (subjective corruption) which accounts for the role of media attention. From the theoretical model we are able to derive testable implications for the empirical analysis, i.e. whether socio and cultural norms can explain the gap between the two measures of corruption across Europe. We employ a generalised setting of the structural equation models to build latent indices of objective and subjective corruption from our microdata exploiting the information on various economic, geographic and socio-demographic factors that can affect the perception and the experience of corruption practices. The resulting indices allow us to define country rankings for both types of corruption and draw a geopolitical picture of the phenomenon across Europe. We also show that countries where the quality of media is higher are associated with lower differences between perceived and real corruption.

JEL Classification: C43, C83, D73, H11, R50.

Keywords: Perceived and experienced corruption, Latent variables, Latent multi-dimensional index, Multiple indicators multiple causes models, Generalized SEM MIMIC.

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# 1 Introduction

Corruption represents one of the greatest threats to economic and social progress around the globe because it undermines the institutional and legal foundations of societies and economic systems. A challenging task of the most recent empirical research on corruption is identifying the right tools of measuring a phenomenon which is not directly observable due to its illegal and clandestine nature: corrupt transactions are typically cloaked in secrecy and can therefore not be systematically recorded (Søreide 2014). One approach is to measure perceptions of corruption: several organisations and research institutions have, in fact, built perception-based indices of corruption across countries to qualitatively assess its incidence. Composite indices of corruption gained increasing popularity, and issues related to these indices also gained considerable attention. The most discussed issue relates to the fact that these corruption indices often rely on the perceptions of experts rather than on objective data (e.g., the Corruption Perception Index of Transparency International and the World Bank's World Governance Indicators<sup>1</sup>). However, some criticism has been raised on the actual capability of perception-based indices to gauge the essence of concepts they aim to measure. For example, the perceived-by-experts quality of institutions might not be necessarily related to the real quality of institutions within a country (Persson 2002; Glaeser et al. 2004; Mocan 2008). Moreover it is difficult to say whether low institutional quality leads to corruption or the other way round, therefore endogeneity is strongly pointed out as a relevant concern (Dreher et al. 2007). Weber Abramo (2008) and Andvig (2005) both argue that perceived corruption is not related to bribery; in fact, perception-based indices are more likely to reflect the quality of a country's institutions and government rather than the real incidence of corruption.

In sum, it has been highlighted that these perception-based indices represent questionable attempts to weld together different types of corruption practices taking place in various settings (Sequeira and Djankov 2014). Corruption cannot be observed directly and perception-based indices -often built on experts' assessment- while useful for raising consciousness of the corruptive

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<sup>1</sup>See Kaufmann et al. (2010).

phenomena, have important drawbacks related to some methodological issues such as voluntary or involuntary misreporting and sampling bias. Therefore, literature largely recognised that perceptions do not accurately reflect the actual level of corruption (Charron 2016).

Recent empirical research tries to overcome the limitations of perception-based country-level indices; on the one hand the search for alternative and less subjective ways to construct indices (Dreher et al. 2007), and on the other hand the development of investigations by exploiting survey micro-level data on ‘actual’ levels of individuals’ experience of corruption (Charron et al. 2014 and 2015; Mocan 2008). Further attempts to gather micro-level data on corruption through questions on bribe payments (i.e., on experience of corruption) have been carried out both at firm and household level, see for example the World Business Enterprise Survey, the Business Environment and Enterprise Performance Survey, the Bribe Payer Index, the Global Corruption Barometer, the International Crime and Victimization Survey, and the recently developed European Quality of Government Index (EQI).<sup>2</sup>

These survey-based measures attempt to elicit truthful reporting of bribes through standardised questions to contextualised respondents’ actions. The measure of experienced corruption<sup>3</sup> generally used is the extent to which average citizens and firms use bribery in dealing with or obtaining public services or in interacting with government officials to obtain a public contract or to do business. As stressed by Dreher et al. (2007) these measures might also be inertial: “once a country is reported to be corrupt, perception about this country may not change, leading future survey respondents to over-estimate true corruption” (p.444). Also in most of these surveys the adopted definition of ‘experience’ within corruption has its own limitations as it usually does not endorse the so called ‘high-level’ or ‘grand’ corruption among elites, party members, and in the public procurement sector (Charron 2016). Increasingly therefore, the preferred approach is relying on more direct

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<sup>2</sup>For a more in depth description of the EQI see Charron et al. (2013; 2014; 2015).

<sup>3</sup>Experience-based indicators measure actual personal experience with corruption. In particular, experience-based measurement tools ask citizens if they have been asked to give an informal payment (i.e., a bribe), or if they have voluntarily offered something to a public officer as a sign of gratitude or simply because they were expected to pay a bribe.

(objective) measures of corruption linked to the actual experience of corruption. Early studies used surveys to measure the perception of bribes. Others asked the bribe-payers themselves, like in a study conducted by Svensson (2003); whilst Olken and Barron (2009) used officials as truck drivers' assistants and sent them with drivers on their daily routes with the task of reporting the bribes paid at every police checkpoint. Experiential data comprise citizens' experiences of corruption and are quite useful to measure the extent and nature of 'petty corruption' (bribes and misbehaviour) in some sectors such as health, education and law enforcement. But the reliability and accuracy of these survey-based measures crucially rely on the quality of the question wording, on the cultural differences among respondents (that may lead to very different interpretations of the same question) and also on the respondents' truthful reporting of bribing (Sequeira 2012).

These points clearly put into question the reliability of survey-based indices of corruption (both perception-based and experience-based indices). We want to measure a phenomenon that is not only covert, but notoriously difficult even to define and to do so we try to define an index of corruption constructed by accounting measurable variables we identify as causes and indicators of the latent variable. Being latent is in fact probably the most important and challenging feature of corruption, therefore Structural Equation Modelling (SEM) is particularly convenient as it explores the covariance structures between the latent variable's observable causes and indicators (Dreher et al. 2007; Buehn and Schneider 2009; Dreher and Schneider 2010). SEM allows to account for causal relationships among indicators. A distinct advantage of this method is that the correlations among the observed indicators are explicitly modelled as the result of underlying common factors that are responsible for the outcomes (i.e., the indicator variables are used to capture the effect of the unobserved variable). More specifically, we adopt a Multiple Indicators Multiple Causes (MIMIC) model under a Generalized Structural Equation Model (GSEM) to account for the geographic and socio-demographic control variables included in our microdata (Corrado and De Michele 2016). In the MIMIC model, beside the 'causal' part, there is the measurement part of the model -which consists of equations which link the latent variable(s) (i.e., corruption) with its indicators- that

recalls a factor analysis, more specifically a confirmatory factor analysis, where several observed indicators are used to represent fewer latent variables (Krishnakumar and Wendelspiess Chávez Juárez 2015). If we are using binomial or ordinal (categorical) responses, then we need a GSEM specification using a binomial probit or an ordered probit model to deal with non-normal microdata (Agresti 2002). Following the recent literature on overcoming the limitations of perception-based indices of corruption (Bollen 2002; Bollen and Davis 2009), we employ a special case of the structural equation models.

Our analysis attempts to answer to the following questions: (i) Can we measure objective and subjective corruption? (ii) What are the alternative approaches for producing cross-country indices of corruption that allow for a meaningful ranking of corruption across countries? (iii) And to which extent country-specific economic, cultural, social and demographic factors are important to capture the gap between actual and perceived levels of corruption in a country?

This paper is structured as follows. Section two provides an overview of the methodological issues behind the measurement of corruption beyond perceptions. Section three illustrates the theoretical model for the corruption decision-making process (objective corruption) and the corruption perception-making process (subjective corruption) and lists the testable hypotheses. Section four and five describe the data and the estimation methodology. Sections six and seven comment the results and the implied country rankings derived from the corruption indices built from the estimated model. Section eight concludes.

## **2 Measuring corruption beyond perceptions**

As observed in the literature, the most challenging issue when dealing with corruption is to build valid and reliable measures since perception-based measures do not seem to ‘tie in with reality’ (see, also, Razafindrakoto and Rouboud 2010; Svensson 2005). This is important for a better understanding of corruption and for detecting possible causes and solutions to this problem (Uslaner

2002; Holmberg et al. 2009; Shleifer and Vishny 1993; Mauro 1995).

What are then the major problems behind these subjective indices? In the first instance, such indices are likely to overstate the degree of corruption the individuals have actually experienced. For example, Razafindrakoto and Roubaud (2010) show that experts, asked to give an estimate of bribery rates in their own countries, grossly exaggerate the percentage of people who actually paid a bribe. In fact, often experts live outside the country that they are assessing and that their views are ideologically biased (Charron 2016). Another problem is that perceptions of corruption are probably influenced by other factors such as individual characteristics, cultural and social norms. In particular, a recent literature investigates the link between mass media and corruption, reporting a bias between corruption and corruption perception due to the influence of mass media (see, among others, Suphachalasai 2005, Melgar et al. 2010, and Rizzica and Tonello 2015). Therefore, we expect that a straightforward consequence of higher quality of media is a lower bias in the difference between corruption and corruption perception, and this might explain the heterogeneity among countries and regions in such a difference. To the best of our knowledge, this is the first paper that empirically investigates the link between the geographic differences in media attention and the perceived corruption bias across Europe.

We assess whether corruption is context-specific thus depending on the institutional setup or on social norms and culture (Lambsdorff and Schulze 2015; Fisman and Miguel 2007; Kis-Katos and Schulze 2014). Data are taken from one the largest multi-country novel survey specifically focusing on governance and corruption at the regional level within the European Union: the EQI. First, these data allow perceptions of European citizens with and without experience of corruption to be compared at both the national and sub-national level.<sup>4</sup> Second, other factors are considered along with corruption perception and experience of corruption which relate to citizens' socio-economic and demographic characteristics, which might actually bias the extent to which individuals perceive

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<sup>4</sup>A regional-level "quality of government" (QoG) index score for 172 NUTS-1 and NUTS-2 regions (Nomenclature des Unités Territoriales Statistiques) within eighteen EU countries was built based on survey questions on citizen perception of QoG.

(*subjective*) corruption relative to the level of actual (*objective*) corruption in the region where they live. A very important driver of the gap between the two measures of corruption might be found in the quality of media. Even if the negative effect of corruption on economic growth is now well established (Aghion et al. 2016; Fisman and Svensson 2007; Mauro 1995, among others), there are still mixed findings in understanding which country-specific characteristics are more linked with corruption and, more specifically, with the gap between perceived and real corruption. Our paper tries to answer this question assuming that the higher is the quality of media the lower is the gap. The questionnaire has been administered to the consumers of everyday public services with about 200 respondents per NUTS-1 or -2 regions and described in more details in Section 4.

### **3 The model**

We model the corruption decision-making process (objective corruption) and the corruption perception-making process (subjective corruption) with two similar approaches. The approaches differ from the influence of media attention. We rely on the assumption that media influence perceptions about corruption across different sectors but do not enter in the corruption decision-making process. On one hand, the media industry may report corruption scandals and arrests to highlight the positive action of the police force, or to put the emphasis on the cultural decline, or to stimulate the political change. Thus, media have a crucial role on the corruption perception-making process. On the other hand, the decision to corrupt is not linked to the media attention on corruption. Our interpretation is consistent with previous theories that link corruption perceptions and corruption levels (Melgar et al. 2010), even though they tend to distinguish these two measures, while we try to differ them simply from the influence of media. Note that our model is static, that is it does not consider the dynamic evolution of corruption perceptions.

### 3.1 Objective corruption

To model the decision of individuals to corrupt, we follow Olken and Pande (2012). In our model, a worker  $i$  works in a sector  $\varphi \in \{Government, Police, Education, Health\}$  and receives a wage  $w_{i,\varphi}$ . The worker can decide to corrupt or be honest. If she decides to be honest, she will receive her wage  $w_{i,\varphi}$ . If she decides to corrupt, with probability  $p_\varphi$  she will be detected, she will be fired and she will receive an outside option  $z_{i,\varphi}$ ; otherwise, with probability  $1 - p_\varphi$  she will not be detected, she will gain her wage  $w_{i,\varphi}$  and the bribe  $b_\varphi$ , and she will be affected by a dishonesty cost  $d_i$ . Thus, the utility of worker  $i$  employed in sector  $\varphi$  writes:

$$U_{i,\varphi}(w_{i,\varphi}, z_{i,\varphi}, p_\varphi, b_\varphi, d_i) = \left\{ \begin{array}{ll} w_{i,\varphi} & \text{if honest} \\ z_{i,\varphi} & \text{if corrupt and detected} \\ w_{i,\varphi} + b_\varphi - d_i & \text{if corrupt and not detected} \end{array} \right\} \quad (1)$$

In equilibrium, the worker will corrupt if and only if:

$$p_\varphi z_{i,\varphi} + (1 - p_\varphi)(w_{i,\varphi} + b_\varphi - d_i) > w_{i,\varphi} \quad (2)$$

that is, if and only if:

$$w_{i,\varphi} - z_{i,\varphi} < \frac{1 - p_\varphi}{p_\varphi}(b_\varphi - d_i) \quad (3)$$

The first ingredient that determines the level of corruption is the difference between wage and the outside option,  $w_{i,\varphi} - z_{i,\varphi}$ . The lower is the wage ( $w_{i,\varphi}$ ), the more likely the worker will be tempted to corrupt. Note that in this context corrupt and being corrupt may be perceived as different actions, and they actually are. However, the model does not change since in the context of corruption the wage plus the bribe paid are interpreted as an increase of the utility and therefore they have the same impact in the case of being corrupt and corrupt. Also, the wage effect might be mitigated by the outside option ( $z_{i,\varphi}$ ). Individuals earning higher wage might have higher outside

option, if we interpret the outside option as the possibility to be defended by good lawyers or protected by the firm owner.

The second parameter affecting the worker's utility is the bribe  $b_\varphi$ . The bribe is a positive number depending on the sector in which the worker is employed. As noted above, we may model the action of corrupting rather than being corrupt if we assume the bribe being a negative number which positively affect the worker's utility. Also, at this stage we assume that for each sector  $\varphi$ , there exists a minimal bribe that makes corruption possible and this is equal to  $b_\varphi$ . This is the optimal sector bribe, that it the bribe such that the worker can corrupt and no higher bribe can give her a strictly higher utility. We will assume each bribe is optimal.

The third fundamental ingredient is the probability of being detected ( $p_\varphi$ ). According to our model, the higher is the probability to be detected, the lower will be the probability to corrupt. This probability is heterogeneous across sectors, that is people with the same characteristics (i.e., wage, dishonesty cost, and outside option) may differ in terms of decision to corrupt simply because the probability of being detected in the sector where they work is different.

The last term,  $d_i$ , represents a dishonesty cost, that is a personal cost associated to the dishonest behaviour, and it is heterogeneous across individuals. The dishonesty cost might also be viewed as a proxy for social and cultural norms, if we think at dishonesty as another way not to cooperate. Therefore, the term  $d_i$  may be influenced by individual socio-demographic characteristics, such as gender, educational level, geography, ethnicity, and social preferences. In particular, the literature linking socio-cultural norms with gender is controversial and depends on the context, even though it seems that women tend to lye less (Swamy et al. 2001; Dreber and Johannesson 2008; Conrads et al. 2013) and cooperate more than men (Molinas 1998; Charness and Rustichini 2011). In addition, several studies (Gatti et al., 2003; Sahin and Sahin, 2010, among others) show that the more educated and the elderly seem to be more averse to corruption than others.

## 3.2 Subjective corruption

When we model the corruption perception-making process, we follow Suphachalasai (2005). This model extends the previous one as it introduces the role of media attention on corruption. We rely on the assumption that media attention about corruption influences the perception about corruption, even though it does not influence the corruption itself. This is supported by Rizzica and Tonello (2015), where the authors suggest that individuals' perception about corruption is biased by media content. However, the direction in which this bias works is not very clear. On the one hand, media negative attention may increase the level of corruption perception as individuals link the quantity of news with the quantity of corruption episodes; on the other hand, news on corruption may be associated with more controls and therefore more probability of being corrupt, and this may work as a proxy of less corruption.

Note that our model does not necessarily imply that corruption and its perception are not correlated with each other. It says that media attention influences corruption perception only, which is ultimately linked with corruption. However, the direction of this link reflects the ambiguity of the relationship between media attention and corruption perception discussed above.

We introduce in our model the probability that a corruption news regarding sector  $\varphi$  appears in the media (namely,  $q_\varphi$ ). We assume that corruption can be detected and/or reported by the media. Thus, if worker  $i$  employed in sector  $\varphi$  decides to corrupt, with probability  $p_\varphi$  she will be detected and with probability  $q_\varphi$  the news about her corruption episode will appear in the media. We also assume that if the news appear in the media, then she will be detected. In this new framework, the incentive compatibility of being honest depends on the probability of not being detected neither by the inspectors nor by the media. Therefore, the utility of worker  $i$  employed

in sector  $\varphi$  writes:

$$U_{i,\varphi}(w_{i,\varphi}, z_{i,\varphi}, p_\varphi, q_\varphi, b_\varphi, k_\varphi, d_i) = \left. \begin{cases} w_{i,\varphi} & \text{if honest} \\ z_{i,\varphi} & \text{if corrupt, detected, and not appeared} \\ z_{i,\varphi} + k_\varphi & \text{if corrupt, detected, and appeared} \\ w_{i,\varphi} + b_\varphi - d_i & \text{if corrupt and not detected and not appeared} \end{cases} \right\} \quad (4)$$

Now we assume that in case the worker is detected and the news about the corruption episode appears in the media, the utility is affected by the outside option plus a constant  $k_\varphi$ , which depends on the sector and may be positive or negative. In the equilibrium the worker  $i$  employed in sector  $\varphi$  will corrupt if and only if:

$$p_\varphi q_\varphi z_{i,\varphi} + p_\varphi(1 - q_\varphi)(z_{i,\varphi} + k_\varphi) + (1 - p_\varphi)(1 - q_\varphi)(w + b_\varphi - d_i) > w_{i,\varphi} \quad (5)$$

that is, if and only if:

$$w_{i,\varphi} - \frac{p_\varphi}{p_\varphi + q_\varphi - p_\varphi q_\varphi}(z_{i,\varphi} + k_\varphi) < \left(\frac{1}{p_\varphi + q_\varphi - p_\varphi q_\varphi} - 1\right)(b_\varphi - d_i) \quad (6)$$

The perception of corruption is positively influenced by the probability of being reported by media. The higher the wage, the lower the level of corruption. However, the outside option is now influenced by the probability of appearing in the media. More precisely, when this probability increases, the weight of the outside option decreases.<sup>5</sup> The interpretation hinges on the assumption that negative media attention decreases the capability to be protected by the outside option. If we interpret the outside option as the network that helps to reduce the risk of being detected or punished, e.g. the quality of your lawyer or the protection you may have from your firm/employer, it is easy to associate the probability of appearing in the media with a lower role of the outside option and therefore with a lower probability of being corrupt. Moreover, the reason why a corrupt

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<sup>5</sup>This comes from the fact that  $\partial_{p_\varphi} \frac{p_\varphi}{p_\varphi + q_\varphi - p_\varphi q_\varphi} < 0$  since  $p_\varphi, q_\varphi \in [0, 1]$ .

person is detected, but the news does not appear in the media, may lie in the quality of media at the local level. Therefore, we assume that the higher is the quality of media, the lower the probability of not being detected in case of corruption, and therefore the higher the outside option. We insert the term  $k_\varphi$  to capture the amplifying effect exerted by the media when corruption episodes are reported. In fact, negative media attention might represent an individual's reputation damage (loss), therefore increasing the value of the outside option.

Also, we may have situations in which the probability of being detected is high even if the probability of being reported in the media is low, or the probability of being detected is low but the probability of appearing in the media is high. These affect both individually and jointly the corruption behaviour as they capture different aspects of the decision-making process.

Similarly, a higher probability of being reported by the media decreases the weight of the utility arising from the bribe, discounted by individual dishonesty cost ( $b_\varphi - d_i$ ). This is consistent with the idea that appearing in the media reduces the probability of being corrupt.

Note that even though corrupting and being corrupt are different behaviours, our model remains valid in both cases. Indeed, when we model the corruption behaviour, the bribe paid becomes a negative number but we can transform our utility with a monotonically decreasing function with respect to the bribe and the analysis holds.

### 3.3 Testable hypotheses

Based on our model, we wish to test the following hypotheses:

*Hypothesis 1: Objective and subjective corruption have the same ranking across sectors*

The first hypothesis we want to test concerns the distribution in the probability of being corrupt across different sectors. Under the null, the distribution of the probability of being corrupt across sectors should be the same for objective and subjective corruption. The distributions of these probabilities, which are not observed, reflect the ranking of the sectors according to the latent corruption levels. However, since the probability of being detected and the corruption news being

reported by the media also affects subjective corruption, the rankings of objective and subjective corruption may differ.

*Hypothesis 2: Higher income decreases corruption*

According to our model, a higher wage should reduce the level of corruption. This hypothesis shares the view of some theoretical studies, such as those of Van Rijckeghem and Weder (2001) among others, who argue that higher wages by raising the cost of job loss due to illicit behavior and by making public employees feel that they are being ‘fairly’ treated, should represent a disincentive for public officials to be corrupt. However, the decision-making process is also affected by the outside option, which is differently weighted depending on the measure of corruption (objective vs subjective). Therefore we expect a different impact of wages on the two latent corruption measures.

*Hypothesis 3: Social norms affect corruption*

We test whether our different measures of social norms, proxied by gender, educational level, geography, ethnicity, and social preferences, have a different impact on the implied measures for objective and subjective corruption. According to our model, social norms influence corruption behaviour through the dishonesty costs which can be associated to the feelings of shame or guilt caused by the norm-breaking. A society with many corruption norm-violating individuals will tend to reinforce corruption compliance attitudes and will have lower dishonesty costs, which may lead to a corruption trap as highlighted by Barr and Serra (2010). As shown by Gatti et al. (2003) and Sahin and Sahin (2010) certain groups – women, the educated and the elderly– seem to be more averse to corruption than others and therefore we expect a correlation between these socio-demographic characteristics and corruption. However, the direction of this influence on the two measures of corruption (subjective and objective) is not univocal as we proxy the dishonesty cost with several social, economic and cultural factors.

## 4 Data

We collect microdata from the first round of the EQI (European Quality of Government Index) a survey of 34,000 residents undertaken across the European Union (EU) countries between 15 December 2009, and 1 February 2010. This study maps-out the variation in Quality of Government (QoG) across Europe both at national and sub-national level using the following pillars of QoG: corruption, protection of the rule of law, government effectiveness and accountability (Charron et al., 2014; 2013). The 2010 EQI index is built for 172 sub-national regions<sup>6</sup> in 18 EU countries.<sup>7</sup> To harmonise the regional aggregation at the sub-national level we refer NUTS1 macroregions which in total are 86. The EQI data have been collected asking questions to European citizens on the QoG, and then aggregated from the individual level to the regional level.<sup>8</sup> The questions are in large part framed around the respondents' experience and their perceptions on the quality of the main public services: education, health services, police force and government agencies and politics. A distinct advantage of this kind of surveys is that they ask detailed and disaggregated questions about corruption at different levels of governance and this might be very useful in identifying priorities for specific policy interventions. Respondents were asked to rate these public services with respect to three related concepts of QoG based on their own experiences as well as perceptions (employed as indicators of the level of corruption in the area): quality, impartiality and the level of corruption of said services. The EQI seeks to capture all regional variation within a country and, as noted in the literature, numerous empirical evidence suggests that the provision and quality of public services, institutions and politics can nonetheless vary substantially across regions and localities (see, for example Martin 2014). We list the data in Table 1.

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<sup>6</sup>The respondents are 195 per each NUTS-1 and NUTS-2 region. EQI also provides design weights equal to the inverse of the size of a region's population within each country, and population weights, so that more (less) populous regions receive greater (lesser) weights to compensate for the fact that their sample size is equal in the survey data.

<sup>7</sup>The regional level for each country included in the survey is based on the European Union's NUTS1 and NUTS 2 statistical regional level (e.g. Nomenclature of Territorial Units for Statistics). NUTS-1 regions are from Germany, U.K., Sweden, Hungary, Greece, the Netherlands and Belgium. NUTS-2 countries are Italy, Spain, Portugal, Denmark, Cz. Republic, Poland, Romania, Bulgaria, Slovakia, France, and Austria.

<sup>8</sup>For more information on the survey and methodology, see Charron et al. (2013, 2014).

[Insert Table 1 about here]

The main questions related to *subjective*<sup>9</sup> and *objective* corruption<sup>10</sup> are the following. For *subjective* corruption:

- Corruption is prevalent in my area's local public school system. (0–10, with '0' strongly disagree - '10' strongly agree)
- Corruption is prevalent in the public health care system in my area. (0–10, with '0' strongly disagree - '10' strongly agree)
- Corruption is prevalent in the in the police force in my area. (0–10, with '0' strongly disagree - '10' strongly agree)
- Please respond to the following: Elections in my area are honest and clean from corruption (0–10, with '0' strongly disagree - '10' strongly agree)

Whilst for *objective* corruption we have collected the following responses to the following question:

- In the past 12 months have you or anyone living in your household paid a bribe in any form to:
  - a. Education services (1 yes/0 no)
  - b. Health or medical services (1 yes/0 no)
  - c. Police (1 yes/0 no)
  - d. Any other government-run agency (1 yes/0 no)

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<sup>9</sup>With respect to corruption perceptions in the public sector, the first four questions listed below are taken and aggregated into a single index of subjective corruption.

<sup>10</sup>In this survey corruption is 'the abuse of entrusted public power for private gain'. This abuse could be by any public employee or politician and the private gain might include money, gifts or other benefits (Charron et al., 2014).

The latter objective responses measure the extent to which average citizens use bribery in dealing with or obtaining public services, it is therefore a ‘self-reported experience’ with corruption.<sup>11</sup> Thus, this definition of ‘experience’ within corruption admittedly has its limits, it refers only to low-level state capture or the so-called ‘petty corruption’ in various public sector services and does not cover the so-called ‘high-level’ corruption among elites or political corruption among party members.

The above variables are employed as indicators of corruption that relate both to individuals’ perception and experience of corruption in the main sectors of the public administration. We use both these predictor variables since as stressed above the correlation between perceived and actual (experience of) corruption might be low since perceived corruption is not related to bribery (Weber Abramo 2008) and therefore it might be *per se* a poor predictor of corruption although, at least for the European countries, these perceptions are highly consistent with actual levels of reported corruption.

For the causes of corruption we gather some additional information at the individual level from socio-demographic factors such as education, age, gender, mother tongue, income and the geographical factors such as the place where respondents reside and live: if it is an urban area and the region it belongs to. These variables capture the social, historical and cultural characteristics of the region that might impact on the pervasiveness of corruption in the area.

[Insert Figure 1 about here]

[Insert Figure 2 about here]

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<sup>11</sup>The survey narrows questions to real experiences, rather than ideas or opinions, in order to get rid of attitudinal bias (Bradburn 1983).

## 5 Econometric model description

The two latent constructs -Objective Corruption and Subjective Corruption- are estimated through GSEM MIMIC models starting from eight socio-demographic and geographic control variables -in common in both models- and four indicators, described in Section four (see Table 1 for the full list of the model variables). Figures 1 to 2 represent the model and all the relationships among variables with path diagrams. In the path diagram, the latent variable is represented with an ellipse, the measured variables with squares and the errors with circles. Each arrow represents a causal connection between variables, or a causal path. A line ending with an arrow indicates a hypothesised direct relationship between the variables. It has to be highlighted that the direction of the arrow does not necessarily indicate the direction of causation. In Figures 1 and 2, the section of the graph below the latent variable represents the causal model of the GSEM MIMIC, whereas the section above the latent construct represents the measurement model.

### 5.1 Model specification and estimation

In the GSEM MIMIC model (Multiple Indicators Multiple Causes; see Joreskog and Goldberger 1975; Rabe-Hesketh et al. 2004; Raiser et al. 2007; Corrado and De Michele 2016) it is not only assumed that the observed variables are manifestations of a latent concept but also that there are other exogenous variables that ‘cause’ and influence the latent factor(s).

The model consists of a ‘causal’ equation that examines the relationships between the latent variables ( $\boldsymbol{\eta}$ ) and observed variables ( $\mathbf{x}$ ) or ‘causes’ subject to a disturbance ( $\mathbf{v}$ ):

$$\boldsymbol{\eta} = \mathbf{B}\mathbf{x} + \mathbf{v} \quad (7)$$

where  $\boldsymbol{\eta}$  is a  $(q \times 1)$  vector of dependent variables (DV),  $\mathbf{x}$  is  $(r \times 1)$  vector of observed variables and  $\mathbf{B}$  is the corresponding  $(q \times r)$  vector of structural parameters relating latent dependent variables to manifest variables and  $\mathbf{v}$  is a  $(q \times 1)$  vector of disturbances. We define as  $\sigma_v^2 \mathbf{I}$  the

covariance matrix of  $\mathbf{v}$ . In our theoretical model, we have one latent variable (i.e., *Corruption*), four indicators of corruption activities (i.e., the bribe  $b_\varphi$ ), and eight ‘causes’ or control variables.<sup>12</sup> In particular, we can write the vector of observed exogenous variables in terms of the socio-demographic characteristics  $d_i$  and the wage  $w_{i,\varphi}$ . Thus, our vector of observed exogenous variables writes  $\mathbf{x} = (d_i, w_{i,\varphi})$ .

In the MIMIC model, besides the ‘causal’ model, there is also a measurement equation specifying how the latent variables ( $\boldsymbol{\eta}$ ) determine the set of latent continuous indicators ( $\mathbf{y}^*$ ) subject to disturbances or errors ( $\mathbf{e}$ ):

$$\mathbf{y}^* = \boldsymbol{\Lambda}_y \boldsymbol{\eta} + \mathbf{e} \quad (8)$$

where  $\mathbf{y}^*$  is the  $(s \times 1)$  vector of indicators,  $\boldsymbol{\Lambda}_y$  is a  $(s \times q)$  factor loading matrix and  $\Theta_{\mathbf{e}}$  is the covariance matrix of  $\mathbf{e}$  which is a  $(s \times 1)$  vector of disturbances. It is assumed that  $E(\mathbf{e}) = \mathbf{0}$  and  $\text{cov}(\mathbf{e}, \boldsymbol{\eta}) = \mathbf{0}$ . For objective corruption,  $\boldsymbol{\Lambda}_y$  captures the probability of being detected,  $p_\varphi$ . While for subjective corruption it captures both the probability of being detected and the probability of appearing in the media,  $p_\varphi$  and  $q_\varphi$ . In our model the latent dependent variable (*Corruption*) determines or ‘drives’ the set of four observable indicators (perceived and experienced level of corruption in the public health care system, education services, police force and other government agencies). Appendix A derives the reduced form model and describes the identification strategy to estimate the structural parameters  $\mathbf{B}$  in equation (7).

Since our data are either binomial or categorical (Lykert type scale) we use a *generalised* model in order to deal with non-normality and the idiosyncratic structure of the data. Differently to the case of continuous responses, maximum likelihood estimation (*ML*) cannot be based on the empirical covariance matrix of the observed responses. Indeed, the likelihood is obtained by integrating out the latent variables.<sup>13</sup> Let  $\boldsymbol{\theta}$  be the  $(t \times 1)$  vector of independent parameters,  $\mathbf{y}$

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<sup>12</sup>The eight geographic and socio-demographic observed variables included in the ‘causal’ model, within the GSEM MIMIC, are age, gender, educational level, income level, mother tongue, urban area, region and country, respectively.

<sup>13</sup>It is to be highlighted that, within STATA 13.1, log-likelihood calculations for fitting any model with latent variables require integrating out the latent variables. The default numerical integration method implemented in

be the vector of observed response variables,  $\mathbf{x}$  be the vector of observed exogenous variables or ‘causes’, and  $\boldsymbol{\eta}$  be the  $(q \times 1)$  vector of latent variables. Then the marginal likelihood can be computed as:

$$\mathcal{L}(\boldsymbol{\theta}) = \int_{\mathfrak{R}^q} f(\mathbf{y}|\mathbf{x}, \boldsymbol{\eta}, \boldsymbol{\theta}) \phi(\boldsymbol{\eta}|\boldsymbol{\mu}_\eta, \boldsymbol{\Omega}) d\boldsymbol{\eta} \quad (9)$$

where  $\mathfrak{R}$  denotes the set of values on the real line,  $\mathfrak{R}^q$  is the analog in a  $q$ -dimensional space,  $f(\cdot)$  is the conditional probability density for the observed responses  $\mathbf{y}$ ,  $\phi(\cdot)$  is the multivariate normal density for  $\boldsymbol{\eta}$ ,  $\boldsymbol{\mu}_\eta$  is the expected value of  $\boldsymbol{\eta}$  and  $\boldsymbol{\Omega}$  is the covariance matrix of  $\boldsymbol{\eta}$ . If we have  $s$  response variables (indicators), the conditional joint density function for a given observation is:

$$f(\mathbf{y}|\mathbf{x}, \boldsymbol{\eta}, \boldsymbol{\theta}) = \prod_{i=1}^s f_i(y_i|\mathbf{x}, \boldsymbol{\eta}, \boldsymbol{\theta}) \quad (10)$$

The advantage of structural equation modelling -also in its generalized form- compared with standard econometric methods, is that SEM uses the full information on causes and indicators of the latent dependent variable. Therefore, the latent construct relates directly to the causes and to the indicators used to specify the model which simultaneously estimates the underlying system of equations and the implied probabilities. After the estimation of our GSEM MIMIC model we need to make a further step in our analysis related to the model evaluation, which is described in Appendix B.

## 6 Results

As Tables 2 and 3 show for perceived -subjective- corruption the public sectors associated with higher corruption listed in a decreasing order of incidence are: public health system, education services (public schools), and police force, followed by other government agencies.<sup>14</sup> These are

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GSEM is the mean-variance adaptive Gauss-Hermite quadrature (MVAGH). This method is based on Rabe-Hesketh et al. (2005).

<sup>14</sup>We take the variable *Government Agencies* as a numéraire comprising all other sectors of public administration.

sectors where illegal and dishonest behaviour/conduct by public officials is more likely to arise according to people's perceptions. However, the order seems to reverse when we look at the objective indicators of corruption. In fact, it is more likely that people experience corruption (e.g., bribery) if they want to get something from the following public sectors (ranked in a decreasing order): the police force, education services and public health care system. The police, with which people are most likely to have frequent contact, is therefore among the worst-evaluated sector followed by the other two institutions/services more close to citizens' day-to-day experience: public education and health care systems (Weber Abramo 2008). We conclude that the objective and subjective corruption show different ranking across sectors and therefore we strongly rejected hypothesis 1.

[Insert Table 2 about here]

[Insert Table 3 about here]

With regard to the other covariates, the dimension of individuals' education attainment and personal income are in order of relevance two factors that negatively and significantly correlates to the level of perceived corruption whilst, for objective corruption, only personal income is significant and the sign reverses. This allows us to strongly reject hypotheses 2. This is a quite interesting result. In fact, understanding how socio-demographic factors affect corruption perceptions is important for two main reasons. First, in absence of reliable cross-country indicators of corruption, researchers frequently rely on perception-based measures to proxy actual corruption. Identifying the reasons why corruption perceptions vary across individuals is relevant to understand potential biases in these perception-based measures. Research that considers income and education as predictors of corruption perceptions usually obtain mixed results. Some studies have shown that the wealthy (Davis et al. 2004) and educated people (Olken 2009) perceive more corruption. But others find the opposite i.e. that wealthy and educated individuals perceive less corruption (Redlawsk and McCann 2005; Tverdova 2011). Our results seem to be in line with the latter

evidence finding that in most European countries the poorer and less educated perceive higher levels of corruption than fellow citizens who are wealthier and better educated. Whilst when we refer to objective corruption the sign of the coefficient reverses: the wealthiest people declare to be victims of corruption. This suggests that for higher-income citizens' perceptions of greater corruption reflect their greater exposure to corruption thus validating the intuition that those most affected by corruption should perceive more of it. Whilst for lower-income people this relationship does not hold, in fact the poor will tend to perceive higher levels of corruption but this does not imply that the disadvantaged necessarily experience corruption more often than their wealthiest counterparts. However, income and education seem to be better predictors of subjective corruption than of objective corruption: educational level is a relevant determinant of the perceived level of corruption (more educated people tend to perceive less corruption)<sup>15</sup> along with the social status (people with higher personal income tend to perceive less corruption).<sup>16</sup>

Among the demographic controls 'age' and 'mother tongue' are both significant and negatively correlated both with perception and experience of corruption. Therefore, we cannot reject hypothesis 3 if we consider education, age, and mother tongue as proxies of social norms. The magnitude of the coefficient of the control 'mother tongue' used as a proxy for ethnicity (nationality/immigration) is higher when we consider objective corruption suggesting that belonging to leading ethnic groups is associated with a lower probability of having experienced corruption. Whilst as ethnic fractionalisation increases the likelihood of corrupt practices seems to rise. These findings are supported by several studies in the field that suggest that corruption is more prevalent in countries and in locations (within country) that are more ethnically fragmented (Mauro 1995; LaPorta et al. 1999; Treisman 2000; Alesina et al. 2003). Viewing ethnic groups as manifestation of a shared culture may render co-ethnics more effective than non-co-ethnics in establishing

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<sup>15</sup>This result might be explained by the fact that more educated people have more information and better capabilities to process it and this might be crucial in shaping perceptions of corruption at individual (micro) level (Redlawsk and McCann 2005; Tverdova 2011; Maeda and Ziegfeld 2015).

<sup>16</sup>This is line with recent analysis highlighting that high individual income could be related to lower perceptions via increased optimism (Puri and Robinson 2007). High-income individuals are also more likely capable of using corrupt institutional structures to their advantage (Gutmann et al. 2015).

co-operative anti-corruptive norms. Also, shared membership may enable co-ethnics to find, and punish, non-cooperators (Kimenyi 2006; Habyarimana et al. 2007).

The geographical dimension is also crucial, both in terms of area where people reside and of region where people live. Residing in an urban area increases the probability of experiencing corruption and also the perception of the widespread of corrupt practices: we can argue that it is not urbanisation *per se* that causes higher corruption but the presence of the central government and other public institutions which seat in the urban areas and that have the major impact on corruption levels. But, it is important not to loose sight of other factors, including regional traditions that influence the level of corruption. The results show that the regional dimension, still lacking in most of the analyses of corruption, is very important in explaining both perceptions and experience of corrupt practices. A subnational distinction of a territory in terms of quantification of the corruption rate across the individual regions of a country could offer an insight of the regional disparities that impact on economic performance of a country, and will be a benefit for the conduct of anti-corruption policies and strategies, such as leniency programs<sup>17</sup>, by governments and institutions both at local and central level.

## 7 Ranking the European countries

We now derive an index of corruption based on estimated parameters of a structural relationship between its observed indicators and causes from the GSEM MIMIC model described in paragraph 5.1. The predicted values -factor scores- are obtained here through an iterative procedure, the empirical Bayes means calculation, also known as posterior means<sup>18</sup> (Skrondal and Rabe-Hesketh, 2004). The predicted corruption score allows to obtain a concise measure of the two measures

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<sup>17</sup>As highlighted by Buccirosi and Spagnolo (2006) leniency may have a deterrent effect on illegal relationships sustained by repeated interaction, thus providing an effective policy against sequential illegal transactions such as corruption.

<sup>18</sup>Prediction of latent variables in generalized linear models involves assigning values to the latent variables. Within this method, the iterative procedure makes use of numerical integration whose multivariate integral is approximated by the mean-variance adaptive Gauss-Hermite quadrature (Skrondal and Rabe-Hesketh, 2009).

of corruption in each country and macroregion<sup>19</sup> and to compare them.<sup>20</sup> Such implied measures provides not only an ordinal ranking of corruption across countries reflecting the nature of the data, but they also provide a meaningful measure of ‘distance’ between countries and regions in the corruption indices. Notably, the estimated parameters, together with the observations (collected at national and regional level) for the causes and indicators of corruption, have been used to derive the factor scores that give the values of the subjective and objective corruption indices across the 86 macroregions and 18 countries in our European sample.

Figures 3 and 4 shows the incidence of actual and perceived corruption at the macroregional level. The large within-country variability in the index supports the argument that only a sub-national distinction of a territory in quantifying corruption and in detecting its determinants, can offer an insight of the regional disparities that impact on the economic performance of the European countries. This, in turn, might greatly help in the conduct of anti-corruption policies by central and local institutions and governments.

Looking at the country level data the resulting ranking, reported in Table 4, is not surprising as the Eastern European countries have higher corruption than their Western counterparts. There, corruption is perceived as pervasive and also everyday practices are heavily burdened by corrupt conduct, in particular in the public sector which is notoriously a breeding ground for corruption. It is well-known that in some Eastern European countries former socialist re-distribution mechanisms have been transformed into networks of privilege for politicians and public officials (European Policy Brief 2010). As for countries lagging behind in the scores (i.e., the most corrupt) concerning both perceptions and experiences of corruption, we find Slovakia, Bulgaria, Romania, and Czech Republic. Whilst, the index shows that among Western European countries Greece is the worst ranked both in terms of perceptions and experiences of corruption; this suggests that in particular

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<sup>19</sup>Macroregions are the European NUTS-1 level regions.

<sup>20</sup>For both subjective and objective corruption we can obtain a single, concise measure of any country’s and macroregion index of corruption - the country’s and macroregion’s factor score - calculating the mean of all the individual subjective and objective corruption factor scores sorted by country and by macroregion. We have checked the robustness of the country and macroregion’s rankings by calculating these indices as weighted means using both design weights and population weights, and we found that the rankings are qualitatively similar.

in Greece a culture of mistrust in institutions and malfeasance is far more extreme than anywhere in Europe. In fact, when some places have been stuck in these feedback loops of corruption for a long time, it is hard to see when a new sense of public morality would be enforced and public confidence would be restored.

We are also interested in understanding the link between the quality of media and the countries with higher gap between the two measures of corruption. We proxy the quality of media with the 2011 World Press Freedom Index.<sup>21</sup> We find a clear evidence supporting the assumption that a higher press freedom is associated with a lower gap between perceived and real corruption. For example, Denmark, Sweden and the Netherlands rank as top European countries with respect to the quality of media according to the 2011 World Press Freedom Index and also have the lower gap between perceived and experienced corruption according to our results. In other words, this supports the idea that a more transparent media sector contributes to reduce the distance between what people think about corruption in their countries and how they behave in reality.

[Insert Table 4 about here]

How do the rest of the Western European economies rank on corruption? For objective corruption we find France and Germany as the least corrupt economies whilst Sweden and the Netherlands lie in the middle. Whilst, quite surprising, for perceived corruption Germany and France glide in the middle of the ranking whilst Denmark, Sweden and the Netherlands are the top ranked (the least perceived as corrupt) economies. These findings are in line with the EU Anti-Corruption Report newly released in 2014 which highlights that Denmark and Sweden had the lowest levels of experience of bribery in the European Union, with less than 1% of respondents in those countries expecting to pay a bribe; and in countries like Germany and France, while more than half of the respondents think corruption is a widespread phenomenon, the actual number of people having had to pay a bribe is very low (European Commission 2014). Results also indicate that

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<sup>21</sup>World Press Freedom Index 2011/2012, retrieved from <https://rsf.org/en/world-press-freedom-index-20112012>.

some European countries in our sample such as Portugal, Italy and UK perform very differently according to the index when we refer either to perceptions or experience of corruption. We might expect that individual experiences tend to be strongly correlated with perceptions of corruption throughout Europe, although in some cases we found that corruption is perceived to be higher than it is ‘actually’ experienced among European citizens. For example, Italy and Portugal, after many years of anti-corruption policies, are nowadays relatively ‘clean’ of corruption when we refer to experiences of petty corruption (i.e., bribing) but they are still perceived to be highly corrupt countries in Western Europe. We should then keep in mind that perceptions indicators are “...most likely best treated as ordinal measures, used to compare how countries or regions rank relative to one another, rather than being used as hard ‘benchmarks’ to assess actual levels of corruption” (Charron 2016, p. 22). As stressed by the EU Anti-Corruption Report 2014 in certain countries, including Portugal and Italy, bribery seems rare but corruption in a broader sense is a serious concern. While personal experience of bribery in these countries is rare, and less acute at local level, the perception of corruption is negatively affected by national political scandals which are amplified by the media. Another striking result is the UK ranking in the level of objective corruption: this country lies behind its Western counterparts (France, Germany, Italy, Denmark, Austria, Spain, and Portugal) thus suggesting that there is wedge between the level of subjective corruption, where the UK is perceived to be one of the most ‘clean’ European countries, and the experience of corruption where, instead, this country performs worse. Although corruption is not as a big problem in the UK as in some parts of Europe such as the European Eastern countries, it seems to be more widespread in the UK than many people perceive.

In Table 5 we test the difference between the objective and the subjective corruption factor scores for each country.<sup>22</sup> We reject the null hypothesis that the two means are equal. In particular, in each country we observe that subjective corruption factor scores are significantly higher

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<sup>22</sup>Country and regional averages are based on individual factor scores that are normalised between 0 and 1 applying the formula  $\frac{(x-x_{\min})}{(x_{\max}-x_{\min})}$  where  $x_{\min}$  and  $x_{\max}$  denote the minimum and maximum of the individual factor scores.

than objective corruption factor scores. This may be interpreted as a negative bias created by the media towards corruption, that is corruption is always perceived higher than the real (i.e., objective) corruption level because of the media negative attention. The media coverage of corruptive phenomena are, indeed, very high given the great attention of people/citizens to this matter and its political significance. The penultimate column in Table 5 ranks the countries according to the difference between subjective and objective corruption factor scores. We observe a higher distance between the two measures in France, Slovakia, Portugal, Germany and Italy, while a lower distance in Denmark, the Netherlands, and Sweden.

[Insert Table 5 about here]

It is also worth noticing that for subjective corruption the health care system constitutes the bulk of illicit practices according to individuals' perceptions but when we turn to the instances of bribery then the dimension where corruption is more widespread is law enforcement followed by education and the health care sector (see Table 6). This confirms that law enforcement institutions (e.g., police force) are more prone to risk of corruption given the nature of their work and the challenges they are exposed to; in particular, police corruption can be manifested in a variety of ways, including petty corruption cases, bureaucratic corruption and corruption linked with criminal groups.

[Insert Table 6 about here]

## 8 Final remarks

This paper has addressed two major research questions: what is the magnitude of corruption and how to measure corruption which is, by its very nature, secretive. Some criticism has been recently raised on the actual capability of perception-based indices to gauge the essence of concepts they

aim to measure. We can argue that perceptions are not fact and could be the reflection of distorted truth. Following the recent literature on overcoming the limitations of perception-based indices of corruption (Bollen 2002; Bollen and Davis 2009), we employ a GSEM to build indices of objective and subjective corruption that account also for the geographic and socio-demographic controls from microdata.

We find that the public sectors associated with higher corruption listed in a decreasing order of incidence are the following: public health system, education services (i.e., public schools) and police force followed by other government agencies. These are sectors where illegal and dishonest behaviour/conduct by public official is more likely to arise, according to people's perceptions. But, the order seems to reverse when we look at the objective indicators of corruption. In fact, it is more likely that people experience corruption if they seek advice or a service from the following public sectors (ranked in a decreasing order): the police force, education services and public health care system. Also the regional dimension, still lacking in most of the analyses of corruption, seems to be a very important factor in explaining both perceptions and experience of corrupt practices. The data used in this analysis collected across 86 European NUTS1-level regions allow to capture such geographical dimension of corruption. The corruption index allows us to define country rankings where Slovakia, Bulgaria, Romania and Czech Republic are among the Eastern European countries lagging behind in the scores (the most corrupt) both in terms of perceptions and experiences of corruption. Whilst, as expected among the Western European countries, Greece is ranked the first worst both in terms of perception and experience of corruption. On the other hand, Continental and Scandinavian countries like France, Germany, Italy, Denmark, Portugal are confirmed as the least corrupt in terms of actual corruption, with some relevant difference when we consider perceived corruption, e.g. for France, Italy and Portugal where perceived corruption is substantially higher. We also find that countries with a higher quality of media, measured by the press freedom, are associated with lower differences between perceived and real corruption.

## References

- [1] Aghion, Philippe, Ufuk Akcigit, Julia Cagé, and William R. Kerr. 2016. “Taxation, Corruption, and Growth.” Special Issue on The Economics of Entrepreneurship. *European Economic Review*, 86 (July): 24-51.
- [2] Agresti, Alen. 2002. *Categorical Data Analysis*. New York: Wiley
- [3] Akaike, Hirotugu. 1987. “Factor Analysis and AIC.” *Psychometrika*, 52:3 (September): 317-332.
- [4] Alesina, Alberto, Arnaud Devleeschauwer, William Easterly, Sergio Kurlat and Romain Wacziarg. 2003. “Fractionalization.” *Journal of Economic Growth*, 8:2 (June): 155-194.
- [5] Andvig, Jens Christopher. 2005. “Experimental Economics and Corruption: A Survey of Budding Research.” In *Global Corruption Report*, eds. Transparency International. Cambridge, UK: Cambridge University Press, 265-267.
- [6] Barr, Abigail and Danila Serra. 2010. “Corruption and Culture: An Experimental Analysis.” *Journal of Public Economics*, 94:11/12: 862-869,
- [7] Bollen, Kenneth A. 2002. “Latent Variables in Psychology and the Social Sciences.” *Annual Review of Psychology*, 53:1 (February): 605-634.
- [8] Bollen, Kenneth A. and Walter R. Davis. 2009. “Causal Indicator Models: Identification, Estimation, and Testing.” *Structural Equation Modeling: A Multidisciplinary Journal*, 16:3 (July): 498-522.
- [9] Bradburn, Norman M. 1983. “Response Effects”. In *Handbook of Survey Research*, eds. Peter H. Rossi, James Wright and Andy B. Anderson. New York, NY: Academic Press, 289-328.
- [10] Buccirosi, Paolo and Giancarlo Spagnolo. 2006. “Leniency Policies and Illegal Transactions.” *Journal of Public Economics*, 90(6): 1281-1297.
- [11] Buehn, Andreas and Friedrich Schneider. 2009. “Corruption and the Shadow Economy: A Structural Equation Model Approach.” The Institute for the Study of Labor (IZA) Discussion Paper No. 4182.
- [12] Charness, Gary and Aldo Rustichini. 2011. “Gender differences in cooperation with group membership.” *Games and Economic Behavior*, 72:1:77-85.
- [13] Charron, Nicholas. 2016. “Do Corruption Measures Have a Perception Problem? Assessing the Relationship Between Experiences and Perceptions of Corruption among Citizens and Experts.” *European Political Science Review*, 8:1 (January):147-171.
- [14] Charron, Nicholas, Lewis Dijkstra and Victor Lapuente. 2015. “Mapping the Regional Divide in Europe: A Measure for Assessing Quality of Government in 206 European Regions.” *Social Indicators Research*, 122:2 (June): 315-346.
- [15] Charron, Nicholas, Lewis Dijkstra and Victor Lapuente. 2014. “Regional Governance Matters: Quality of Government within European Union Member States.” *Regional Studies*, 48:1: 68-90.

- [16] Charron, Nicholas, Victor Lapuente and Bo Rothstein. 2013. *Good Government and Corruption from a European Perspective: A Comparative Study on the Quality of Government in EU Regions*. Cheltenham, UK: Edward Elgar Publishing.
- [17] Conrads, Julian, Bernd Irlenbusch, Rainer Michael Rilke and Gari Walkowitz. 2013. "Lying and Team Incentives." *Journal of Economic Psychology*, 34:1-7.
- [18] Corrado, Luisa and Giuseppe De Michele. 2016. "Mind the Gap: Identifying Latent Objective and Subjective Multi-dimensional Indices of Well-Being." CEIS Working Paper No. 386. Available at SSRN: <https://ssrn.com/abstract=2800142>.
- [19] Davis, Charles L., Roderic Ai Camp, R.A. and Kenneth M. Coleman. 2004. "The Influence of Party Systems on Citizens' Perceptions of Corruption and Electoral Response in Latin America." *Comparative Political Studies*, 37:6, (August): 677-703.
- [20] Dreber, Anna and Magnus Johannesson. 2008. "Gender Differences in Deception." *Economics Letters*, 99:1:197-199.
- [21] Dreher, Axel and Friedrich Schneider. 2010. "Corruption and the Shadow Economy: An Empirical Analysis." *Public Choice*, 144:1 (July): 215-238.
- [22] Dreher, Axel, Christos Kotsogiannis and Steve McCorrison. 2007. "Corruption Around the World: Evidence from a Structural Model." *Journal of Comparative Economics*, 35:3 (September): 443-466.
- [23] European Commission. 2014. *EU Anti-Corruption Report*. Brussels: European Commission. Available at: [http://ec.europa.eu/dgs/home-affairs/e-library/documents/policies/organized-crime-and-human-trafficking/corruption/docs/acr\\_2014\\_en.pdf](http://ec.europa.eu/dgs/home-affairs/e-library/documents/policies/organized-crime-and-human-trafficking/corruption/docs/acr_2014_en.pdf) (accessed 15 June 2016).
- [24] European Policy Brief. 2010. *Crime and Culture: Seeing Corruption Comparative Research on Perceptions of Corruption in Bulgaria, Croatia, Germany, Greece, Romania, Turkey and the United Kingdom*, April, European Research Area Socio-economic Sciences and Humanities (SSH). Available at: [http://ec.europa.eu/research/social-sciences/policy-briefs\\_en.html](http://ec.europa.eu/research/social-sciences/policy-briefs_en.html) (accessed 15 June 2016).
- [25] Fisman, Raymond and Jakob Svensson. 2007. "Are Corruption and Taxation Really Harmful to Growth? Firm Level Evidence." *Journal of Development Economics*, 83:1 (May): 63-75.
- [26] Fisman, Raymond and Edward Miguel. 2007. "Corruption, Norms, and Legal Enforcement: Evidence from Diplomatic Parking Tickets." *Journal of Political Economy*, 115:6 (December), 1020-1048.
- [27] Gatti, Roberta, Stefano Paternostro and Jamele Rigolini. 2003. "Individual Attitudes toward Corruption: Do Social Effects Matter?" World Bank Policy Research Working Paper No. 3122. Available at SSRN: <https://ssrn.com/abstract=636542> (accessed 15 June 2016).
- [28] Glaeser, Edward L., Rafael La Porta, Florencio Lopez-de-Silanes and Andrei Shleifer. 2004. "Do Institutions Cause Growth?" *Journal of Economic Growth*, 9:3 (September): 271-303.
- [29] Gutmann, Jerg, Fabio Padovano and Stefan Voigt. 2015. "Perception vs. Experience: Explaining Differences in Corruption Measures Using Microdata, mimeo. Retrieved 10 September, 2016 ([http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2659349](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2659349)).

- [30] Habyarimana, James, Macartan Humphreys, Daniel N. Posner and Jeremy M. Weinstein. 2007. "Why Does Ethnic Diversity Undermine Public Goods Provision?" *American Political Science Review*, 101:4 (November): 709-725.
- [31] Holmberg, Sören, Naghmeh Nasiritousi and Bo Rothstein. 2009. "Quality of Government: What You Get." *Annual Review of Political Science*, 13:12 (August): 35-161.
- [32] Hooper, Daire, Joseph Coughlan and Michael Mullen. 2008. "Structural Equation Modelling: Guidelines for Determining Model Fit." *Electronic Journal of Business Research Methods*, 6:1 (September): 53-60.
- [33] Hu, Li-tze and Peter M. Bentler. 1999. "Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives." *Structural Equation Modeling*, 6:1 (November): 1-55.
- [34] Joreskog, Karl G. and Arthur S. Goldberger. 1975. "Estimation of a Model with Multiple Indicators and Multiple Causes of a Single Latent Variable." *Journal of American Statistical Association*, 70:351a: 631-639.
- [35] Kaufmann, Daniel, Aart Kraay and Massimo Mastruzzi. 2010. "The Worldwide Governance Indicators: A Summary of Methodology, Data and Analytical Issues." World Bank Policy Research Working Paper No. 5430, The World Bank: Washington D.C.
- [36] Kimenyi, Mwangi S. 2006. "Ethnicity, Governance and the Provision of Public Goods." *Journal of African Economies*, 15 (supplement 1): 62-99.
- [37] Kis-Katos, Krisztina and Günther G. Schulze. 2014. "Context-Specificity of Economic Research: The Example of Corruption Research in Southeast Asia," *Reflecting Methodology in Southeast Asian Studies*, eds. Mikko Huotari, Jürgen Rüländ and Judith Schlehe, Houndsmills, Basingstoke: Palgrave Macmillan, 187-210.
- [38] Kline, Rex B. 2011. *Principles and Practice of Structural Equation Modeling*. New York: The Guilford Press.
- [39] Krishnakumar, Jaya and Florian Wendelspiess Chavez Juarez. 2015. "Estimating Capabilities with Structural Equation Models: How Well Are We Doing in a Real World?" *Social Indicators Research*, October, doi:10.1007/s11205-015-1148-6.
- [40] LaPorta, Rafael, Florencio Lopez-de-Silanes, Andrei Shleifer and Robert Vishny. 1999. "The Quality of Government." *Journal of Law, Economics and Organization* 15:1: 222-279.
- [41] Lambsdorff, Johann Graf and Günther Schulze. 2015. "Guest Editorial: Special Issue on Corruption at the Grassroots-level. What Can We Know About Corruption? A Very Short History of Corruption Research and a List of What We Should Aim For." *Jahrbücher f. Nationalökonomie u. Statistik*, 235:2: 100-114.
- [42] Maeda, Kentaro and Adam Ziegfeld. 2015. "Socioeconomic Status and Corruption Perceptions Around the World." *Research and Politics*, 2:2:1-9.
- [43] Martin, Ron. 2014. "Keys to the City: How Economics, Institutions, Social Interaction, and Politics Shape Development." *Economic Geography*, 90: 341-344.

- [44] Mauro, Paolo. 1995. "Corruption and Growth." *The Quarterly Journal of Economics*, 110:3: 681–712.
- [45] Melgar, Natalia, Máximo Rossi and Tom W. Smith. 2010. "The Perception of Corruption." *International Journal Public Opinion Research*, 22:1:120-131.
- [46] Mocan, Naci. 2008. "What Determines Corruption? International Evidence from Microdata." *Economic Inquiry*, 46:4: 493-510.
- [47] Molinas, José R. 1998. "The Impact of Inequality, Gender, External Assistance and Social Capital on Local-Level Cooperation." *World Development*, 26:3:413-431.
- [48] Olken, Benjamin. 2009. "Corruption Perceptions vs. Corruption Reality." *Journal of Public Economics*, 93: 950-964.
- [49] Olken, Benjamin and Patrick Barron. 2009. "The Simple Economics of Extortion: Evidence from Trucking in Aceh." *Journal of Political Economy*, 117:3: 417-452.
- [50] Olken, Benjamin and Rohini Pande. 2012. "Corruption in Developing Countries." *Annual Review of Economics*, 4:1: 479-509.
- [51] Persson, Torsten. 2002. "Do Political Institutions Shape Economic Policy?" *Econometrica*, 7:3 (May): 883-905.
- [52] Puri, Manju and David T. Robinson. 2007. "Optimism and Economic Choice." *Journal of Financial Economics*, 86:1: 71-99.
- [53] Rabe-Hesketh, Sophia, Skrondal, Anders and Andrew Pickles. 2005. "Maximum Likelihood Estimation of Limited and Discrete Dependent Variable Models with Nested Random Effects." *Journal of Econometrics*, 128: 301-323.
- [54] Rabe-Hesketh, Sophia, Skrondal, Anders and Andrew Pickles. 2004. "Generalized Multilevel Structural Equation Modeling." *Psychometrika*. 69: 167–190.
- [55] Raiser, Martin, Di Tommaso, Maria Laura and Melvyn Weeks. 2007. "Home Grown or Imported? Initial Conditions, External Anchors and the Determinants of Institutional Reforms in the Transition Economies." *The Economic Journal*, 117: 858-881.
- [56] Razafindrakoto, Mireille and François Roubaud. 2010. "Are International Databases on Corruption reliable? A Comparison of Expert Opinion Surveys and Household Surveys in Sub-Saharan Africa." *World Development*, 38:8:1057-1069.
- [57] Redlawsk, David P. and James A. McCann. 2005. "Popular Interpretations of 'Corruption' and their Partisan Consequences." *Political Behavior*, 27:3: 261-283.
- [58] Rizzica, Lucia and Marco Tonello. 2015. "Exposure to Media and Corruption Perceptions". Bank of Italy Working Paper 1043.
- [59] Sahin, Ismail and Bahadir Sahin. 2010. "Corruption in US States: the Effects of Socio-Economic Factors." *International Journal of Public Policy*, 6: 3/4: 288-306.

- [60] Sequeira, Sandra. 2012. “Advances in Measuring Corruption in the Field.” In *New Advances in Experimental Research on Corruption*, eds Danila Serra and Leonard Wantchekon, UK: Emerald Group Publishing, 145-175.
- [61] Sequeira, Sandra and Simeon Djankov. 2014. “Corruption and Firm Behavior: Evidence from African Ports.” *Journal of International Economics*, 94:2: 277-294.
- [62] Shleifer, Andrei and Robert W. Vishny. 1993. “Corruption.” *The Quarterly Journal of Economics*, 108:3: 599–617.
- [63] Skrondal, Anders and Sophia Rabe-Hesketh. 2004. *Generalized Latent Variable Modeling: Multilevel, Longitudinal, and Structural Equation Models*. Boca Raton, FL: Chapman & Hall/CRC.
- [64] Skrondal, Anders and Sophia Rabe-Hesketh. 2009. “Prediction in Multilevel Generalized Linear Models.” *Journal of the Royal Statistical Society (A)*, 172: 659-687.
- [65] Søreide, Tina. 2014. *Drivers of Corruption: A Brief Review*. Washington, DC: The World Bank Group. Available at: <https://openknowledge.worldbank.org/handle/10986/20457>. License: CC BY 3.0 IGO (accessed 15 June 2016).
- [66] Suphachalasai, Suphachol. 2005. “Bureaucratic Corruption and Mass Media.” Environmental Economy and Policy Research Working Papers No 05, Department of Land Economics, University of Cambridge, UK.
- [67] Svensson, Jakob. 2005. “Eight Questions about Corruption.” *Journal of Economic Perspectives*, 19:3: 19-42.
- [68] Svensson, Jakob. 2003. “Who Must Pay Bribes and How Much? Evidence from a Cross Section of Firms.” *Quarterly Journal of Economics*, 118:1: 207-30.
- [69] Swamy, Anand, Stephen Knack, Young Lee and Omar Azfar. 2001. “Gender and Corruption.” *Journal of Development Economics*, 64:1 (February): 25-55.
- [70] Treisman, Daniel. 2000. “The Causes of Corruption: a Cross-National Study.” *Journal of Public Economics*, 76:3: 399-457.
- [71] Tverdova, Yuliya. 2011. “See No Evil: Heterogeneity in Public Perceptions of Corruption.” *Canadian Journal of Political Science*, 44:1: 1-25.
- [72] Ullman, Jodie B. 2007. “Structural Equation Modeling.” In *Using Multivariate Statistics*, eds. Barbara J. Tabachnick and Linda S. Fidell, New York: Allyn Bacon, 676-780.
- [73] Uslaner, Eric. 2002. *The Moral Foundations of Trust*. Cambridge, UK: Cambridge University Press.
- [74] Van Rijckeghem, Caroline and Beatrice Weder. 2001. “Bureaucratic Corruption and the Rate of Temptation: do Wages in the Civil Service Affect Corruption and by How Much?” *Journal of Development Economics*, 65: 307-331.
- [75] Weber Abramo, Claudio. 2008. “How Much Do Perceptions of Corruption Really Tell Us?” *Economics: The Open-Access, Open-Assessment E-Journal*, 2:3: 1-56.

## Appendix A

In the EQI dataset we are using, the observed discrete indicators are generalised responses or outcomes. The observed variables used to estimate the GSEM MIMIC model for ‘Objective’ Corruption assume the form of binomial responses (yes/no) and the link function associated to the binomial family in our model is the probit link. Differently, with respect to ‘Subjective’ Corruption, the individual data we are using are categorical (ordinal).

An observed value in the stacked in the vector of the observed responses  $y$  is denoted by  $y_i$ , while the expected value of  $y$  is indicated by  $\mu$ . For the ordinal family we refer to a linear prediction, denoted by  $z$ , in place of the expected value,  $\mu$ . The ordinal family is a discrete response model where the categorical response for  $y$  is assumed to take one of  $k_y$  unique values<sup>23</sup>  $1, 2, \dots, k_{y-1}, k_y$ . The ordinal family with  $k_y$  outcomes has cut-points  $\mu_0, \mu_1, \dots, \mu_{y-1}, \mu_y$ , where  $\mu_0 = -\infty, \dots, \mu_y = +\infty$ . Given the linear prediction  $z$ , the probability that  $y_i$  takes the observed value  $k_y$  is, therefore:

$$\Pr(y_i = k_{y-1}) = \Pr(y_i^* < \mu_{y-2} - z) - \Pr(y_i^* < \mu_{y-1} - z) \quad (\text{A.1})$$

where  $y_i^*$  is the latent component for  $y_i$  and the distribution for  $y_i^*$  is determined by the link function. Typical choice of the link function for categorical responses is the (ordered) probit link. Within GSEM, the probit link assigns  $y_i^*$  the standard normal distribution. Except for the ordinal family, the link function defines the transformation between the mean and the linear prediction for a given response. If  $y_i^*$  is the variable corresponding to an observed discrete response variable  $y_i$ , then the link function performs the transformation:

$$g(\mu) = z \quad (\text{A.2})$$

where  $\mu = E(y_i)$  and  $z$  is the linear prediction.<sup>24</sup>

In our model the latent dependent variable (Corruption) determines or ‘drives’ the set of four observable indicators (perceived and experienced level of corruption in the public health care system, education services, police force and other government agencies). Since  $\boldsymbol{\eta}$  is unobserved it is not possible to recover direct estimates of the structural parameters  $\mathbf{B}$ . However, by substituting in (8) the ‘causal’ model in (7) and the corresponding link function we obtain the reduced form for  $z$ :

$$g(\mu) = \boldsymbol{\Lambda}_y (\mathbf{B}\mathbf{x} + \mathbf{v}) + \mathbf{e} = \boldsymbol{\Pi}\mathbf{x} + \boldsymbol{\varepsilon} \quad (\text{A.3})$$

where  $\boldsymbol{\Pi} = \boldsymbol{\Lambda}_y \mathbf{B}$  is the  $(s \times r)$  reduced form coefficient matrix and the reduced form disturbance vector is  $\boldsymbol{\varepsilon} = \boldsymbol{\Lambda}_y \mathbf{v} + \mathbf{e}$  with covariance matrix:

$$\boldsymbol{\Omega} = E(\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}') = E[(\boldsymbol{\Lambda}_y \mathbf{v} + \mathbf{e})(\boldsymbol{\Lambda}_y \mathbf{v} + \mathbf{e})'] = \sigma_v^2 \boldsymbol{\Lambda}_y \boldsymbol{\Lambda}_y' + \Theta_e \quad (\text{A.4})$$

However, we cannot separately identify  $\boldsymbol{\Lambda}_y$  and  $\mathbf{B}$  in the reduced form matrix  $\boldsymbol{\Pi} = \boldsymbol{\Lambda}_y \mathbf{B}$ .<sup>25</sup> This evidence is a consequence of the fact that the latent variable Corruption is not directly observable. To achieve identification we normalise one of the coefficient in the factor loadings  $\boldsymbol{\Lambda}_y$  such that the unit of measurement of the latent factor  $\boldsymbol{\eta}$  is defined relative to one of the observed indicator variables (see also Raiser et al. 2007). We follow the latter route of identification, fixing to 1 the coefficient of subjective and objective corruption in government agencies/election.

<sup>23</sup>In our model,  $k = 11$ . The individual discrete response  $y_i$  associated to the four indicators underlying the latent Corruption, are expressed in a Likert-type scale through eleven integers, ranging from 0 to 10.

<sup>24</sup>The likelihood function uses the inverse of the link function to map the linear prediction to the mean.

<sup>25</sup>Note that the reduced form parameters are invariant to a transformation given for example by  $\boldsymbol{\Lambda}_y/c$ ,  $\mathbf{B}/c$  and  $\sigma_v^2/c$  where  $c$  is a scalar.

## Appendix B

After the estimation of our GSEM MIMIC model we need to make a further step in our analysis related to the model evaluation. In other words, we are interested in assessing if the model estimated through GSEM MIMIC is also a good model in terms of fit. We cannot directly answer this question because of the limitation of goodness-of-fit indexes availability under GSEM.<sup>26</sup> Therefore, we propose an indirect method which use two different models running on the same dataset – bootstrapped SEM and GSEM MIMIC – comparing them through their relative *AIC*, a predictive fit index available for both methods (Corrado and De Michele 2016). Smaller *AIC* values indicate a good-fitting and parsimonious model.

When using GSEM estimation instead of SEM, we can observe a significant improvement in the overall fit of the model. Taking into account the SEM goodness-of-fit indices reported in Table 2 and Table 3, we can state that the fit of the model for both subjective and objective corruption is above the acceptance thresholds. It has to be underlined that the *AIC* of GSEM is always lower than the SEM *AIC* for the two analysed models. Therefore, we can reasonably conclude that GSEM models satisfy the cut-off criteria for acceptable model fit<sup>27</sup> implying that the GSEM estimations ensure a better fit of the models, compared to the SEM running on the same dataset. The Akaike Information Criterion (*AIC*; Akaike 1987) formula presented in the SEM literature to which we refer is:

$$AIC = \chi_M^2 - 2df_M \quad (B.1)$$

where  $\chi_M^2$  is the model chi-squared, known as the likelihood ratio  $\chi^2$  or generalized likelihood ratio. The index decreases the  $\chi_M^2$  by a factor of twice the model degrees of freedom. The  $\chi^2$  value is the traditional measure for evaluating the overall model fit (Hu and Bentler 1999). If  $\chi_M^2 = 0$ , the model perfectly fits the data (each observed covariance equals its counterpart implied by the model). If the fit of an overidentified model, which is not correctly specified, becomes increasingly worse, then the value of  $\chi_M^2$  increases. Therefore,  $\chi_M^2$  is scaled as a 'badness-of-fit' statistic. The key is that the relative change in the *AIC* is a function of model complexity. It has to be noted that the relative correction for parsimony of the *AIC* becomes smaller and smaller as the sample size increases (Kline 2011). Smaller values correspond to a good-fitting and parsimonious model. Specifically, the selected model will present relatively better fit and fewer free parameters, compared with competing models. It has to be stressed that there is no fixed threshold value for the *AIC*. Therefore, 'small' is intended as a relative term to compare with a second model *AIC*. This method is useful for cross-validation because it is not dependent on sample data (Ullmann 2007).

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<sup>26</sup>Most of SEM post-estimation tests and indices are not available after GSEM because of the assumption of joint-normality of the observed variables.

<sup>27</sup>According to Hooper et al. (2008), the cut-off criteria for acceptable model fit are: values greater 0.9 for CFI; values less than 0.07 for RMSEA; values less than 0.08 for SRMR. Low  $\chi^2$  relative to degrees of freedom, with an insignificant p-value, is the criterion to assess the absolute fit of a model.

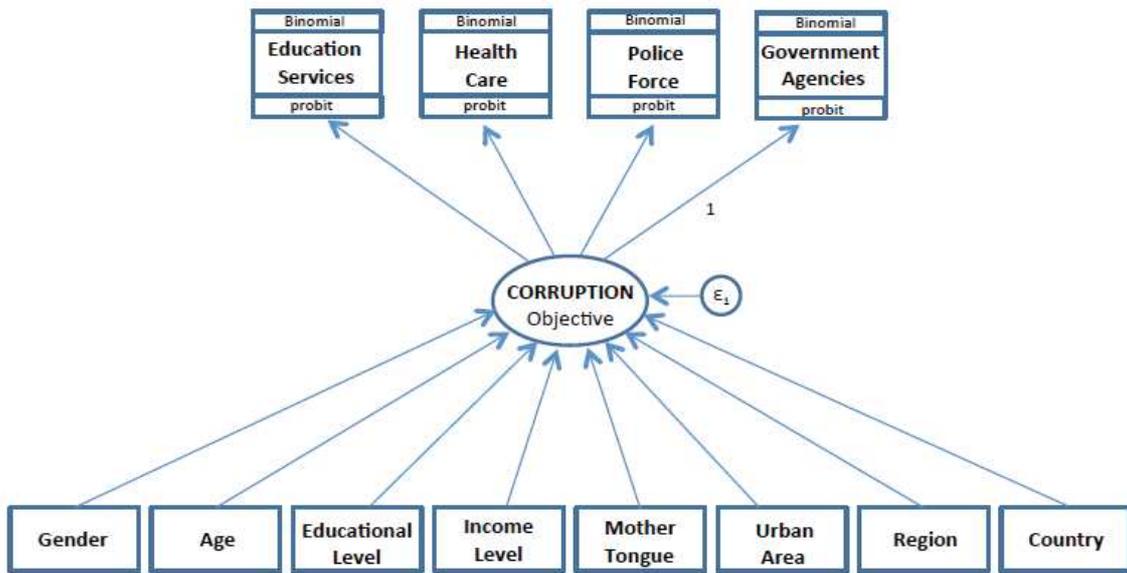


Figure 1: Path Diagram GSEM MIMIC: Objective Corruption

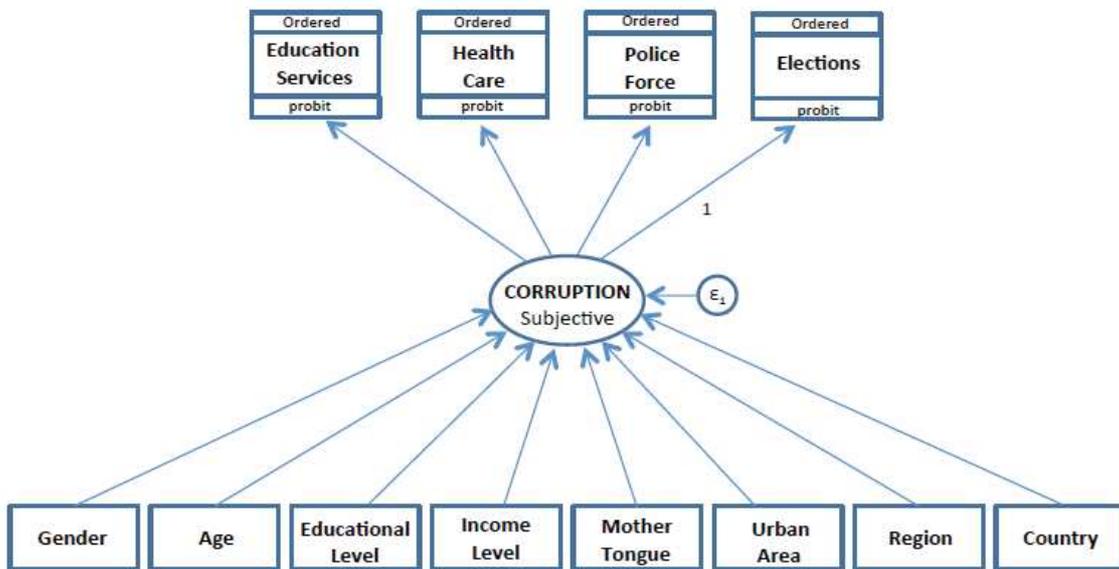


Figure 2: Path Diagram GSEM MIMIC: Subjective Corruption

### Objective corruption in Europe EQI Data 2010

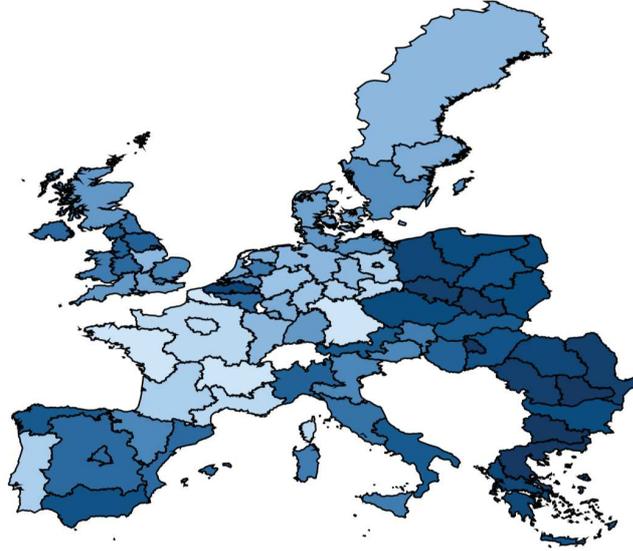


Figure 3: Objective corruption across European NUTS-1 regions. Note: Regions with a darker shade have higher actual corruption levels.

### Subjective corruption in Europe EQI Data 2010

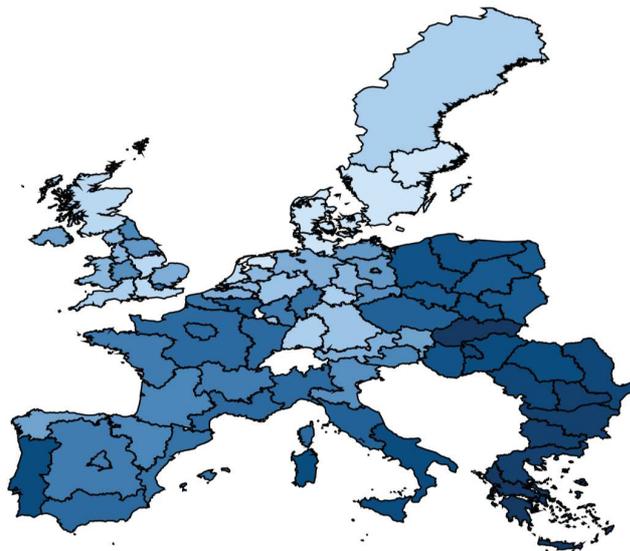


Figure 4: Subjective corruption across European NUTS-1 regions. Note: Regions with a darker shade have higher perceived corruption levels.

Table 1: List of Variables

Variables	Categories	Description
<i>INDICATORS FOR SUBJECTIVE CORRUPTION</i>		
Education Services	Categorical ord.	Corruption is prevalent in my area's local public school system; scale 0-10, with '0' "strongly disagree" and '10' "strongly agree".
Health Care	Categorical ord.	Corruption is prevalent in the public health care system in my area; with scale 0-10, '0' "strongly disagree" and '10' "strongly agree".
Police Force	Categorical ord.	Corruption is prevalent in the police force in my area; scale 0-10, with '0' "strongly disagree" and '10' "strongly agree".
Elections	Categorical ord.	Elections in my area are unfair and corrupt; scale 0-10, with '0' "strongly disagree" and '10' "strongly agree".
<i>INDICATORS FOR OBJECTIVE CORRUPTION</i>		
Education Services	Binary	Dummy if In the past 12 months the respondent or anyone in the household paid a bribe to get education services. 1=Yes 0=No.
Health Care	Binary	Dummy if In the past 12 months the respondent or anyone in the household paid a bribe to get health/medical services. 1=Yes 0=No.
Police Force	Binary	Dummy if In the past 12 months the respondent or anyone in the household paid a bribe to police. 1=Yes 0=No.
Government Agencies	Binary	Dummy if In the past 12 months the respondent or anyone in the household paid a bribe to any government agency. 1=Yes 0=No.
<i>SOCIO-DEMOGRAPHIC CONTROLS</i>		
Gender	Binary	Respondent gender 1=Male; 0=Female.
Age	Continuous	Variable values from 18 to 98.
Educational Level	Categorical ord.	Respondent's highest level of education: 1 (Low: Primary/High School); 2 (Medium: College/University); 3 (High: Master/Doctorate).
Income Level	Categorical ord.	Average total household net income after taxes (per month): 1 (Low); 2 (Average/Median); 3 (High).
Mother tongue	Binary	Dummy if your first language (mother tongue) is the same as the official language in your region. 1=Yes 0=No
<i>GEOGRAPHIC CONTROLS</i>		
Regions	Continuous	Variable values from 1 to 172 for NUTS-1 and NUTS-2 areas and regions.
Urban area	Binary	Dummy for Rural/Small town or city = 0; Large city or urban area/Very large city or urban area=1.
Country	Continuous	Variable values from 1 to 18 for Austria, Belgium, Bulgaria, Czech republic, Denmark, France, Germany, Greece, Hungary, Italy, Netherlands, Poland, Portugal, Romania, Slovakia, Spain, Sweden and UK.

Data source: EQI (2010).

Table 2: Table: GSEM and SEM estimated parameters - Objective Corruption

<i>Indicators</i>	GSEM (Unst.)		SEM (Unst.)		SEM (Stand.)	
Education Services	0.862***	(0.070)	0.757***	(0.058)	0.481***	(0.025)
Health Care	0.806***	(0.068)	1.462***	(0.104)	0.450***	(0.018)
Police Force	0.877***	(0.069)	0.794***	(0.057)	0.500***	(0.027)
Government Agencies	1 (constrained)		1 (constrained)		0.571***	(0.024)
<i>Controls</i>	<i>GSEM Causes</i>		<i>SEM Covariances</i>		<i>SEM Correlations</i>	
Gender	0.086*	(0.042)	0.001***	(0.0003)	0.032***	(0.009)
Age	-0.006***	(0.001)	-0.062***	(0.009)	-0.055***	(0.008)
Educational Level	-0.013	(0.031)	0.001*	(0.0004)	0.021**	(0.008)
Income Level	0.069*	(0.032)	0.001**	(0.0004)	0.024**	(0.008)
Mother Tongue	-0.426***	(0.085)	-0.001***	(0.0003)	-0.043***	(0.011)
Urban Area	0.210***	(0.049)	0.001***	(0.0002)	0.051***	(0.008)
Regions	√		√		√	
Country	√		√		√	
$R^2_{overall}(CD)$	0.579					
$\chi^2_M$	(26), 346.34, p=0.00					
CFI	0.966					
RMSEA	0.021					
SRMR	0.010					
AIC (SEM)	750073					
AIC (GSEM)	20870					
Observations	28607					
logLikelihood (SEM)	-375016					
logLikelihood (GSEM)	-10419					

Standard errors in round parentheses

\*p<0.05; \*\*p<0.01; \*\*\*p<0.001

Data source: EQI (2010)

RMSEA=Root mean squared error of approximation; CFI=Comparative fit index; CD=Coefficient of determination = $R^2$ ;  $\chi^2_M = Model\chi^2$ .

Note: The GSEM is intended here as a binomial probit MIMIC model (Multiple Indicators Multiple Causes) whereas the SEM considered is a bootstrapped SEM (500 reps.) with robust standard errors.

Table 3: Table: GSEM and SEM estimated parameters - Subjective Corruption

<i>Indicators</i>	GSEM (Unst.)		SEM (Unst.)		SEM (Stand.)	
Education Services	5.273***	(0.142)	3.278***	(0.102)	0.787***	(0.004)
Health Care	5.956***	(0.166)	3.648***	(0.113)	0.829***	(0.004)
Police Force	4.745***	(0.126)	3.335***	(0.102)	0.765***	(0.005)
Elections	1 (constrained)		1 (constrained)		0.229***	(0.007)
<i>Controls</i>	<i>GSEM Causes</i>		<i>SEM Covariances</i>		<i>SEM Correlations</i>	
Gender	-0.002	(0.004)	-0.005*	(0.002)	-0.013*	(0.006)
Age	-0.001***	(0.0001)	-0.680***	(0.078)	-0.057***	(0.006)
Educational Level	-0.035***	(0.003)	-0.043***	(0.004)	-0.083***	(0.006)
Income Level	-0.026***	(0.003)	-0.047***	(0.004)	-0.093***	(0.007)
Mother Tongue	-0.018*	(0.008)	-0.003**	(0.001)	-0.016**	(0.006)
Urban Area	0.038***	(0.005)	0.014***	(0.002)	0.046***	(0.006)
Regions	✓		✓		✓	
Country	✓		✓		✓	
R <sup>2</sup> <i>overall</i> (CD)	0.841					
$\chi^2_M$	(26), 803.69, p=0.00					
CFI	0.979					
RMSEA	0.032					
SRMR	0.013					
AIC (SEM)	1461000					
AIC (GSEM)	444600					
Observations	28791					
logLikelihood (SEM)	-730677					
logLikelihood (GSEM)	-222248					

Standard errors in round parentheses

\*p<0.05; \*\*p<0.01; \*\*\*p<0.001

Data source: EQI (2010)

RMSEA=Root mean squared error of approximation; CFI=Comparative fit index; CD=Coefficient of determination =R<sup>2</sup>;  $\chi^2_M = Model\chi^2$ .

Note: The GSEM is intended here as an ordered probit MIMIC model (Multiple Indicators Multiple Causes) whereas the SEM considered is a bootstrapped SEM (500 reps.) with robust standard errors.

Table 4: Rank by Country for predicted Corruption (GSEM)

Subjective Corruption	Objective Corruption
Greece	Greece
Slovakia	Romania
Bulgaria	Poland
Romania	Bulgaria
Portugal	Slovakia
Hungary	Hungary
Poland	Czech Rep.
Czech Rep.	The Netherlands
Italy	Sweden
France	Belgium
Belgium	UK
Spain	Austria
Austria	Spain
Germany	Portugal
UK	Denmark
The Netherlands	Italy
Sweden	Germany
Denmark	France

Countries are ranked from the most to the least corrupt based on the GSEM normalised factor scores.

Table 5: Subjective and objective corruption factor scores (mean)

Country	Subjective		Objective		Diff. ( $H_a \neq 0$ )	Obs.
	Corruption (mean)	Std. Dev.	Corruption (mean)	Std. Dev.		
France	0.627	(0.0019)	0.087	(0.0014)	0.540***	4,532
Slovakia	0.734	(0.0034)	0.229	(0.0052)	0.504***	644
Portugal	0.667	(0.0035)	0.170	(0.0012)	0.497***	1,254
Germany	0.604	(0.0026)	0.113	(0.0016)	0.493***	2,766
Italy	0.644	(0.0025)	0.156	(0.0025)	0.489***	3,161
Bulgaria	0.727	(0.0036)	0.253	(0.0045)	0.474***	1,096
Greece	0.746	(0.0058)	0.290	(0.0068)	0.456***	506
Hungary	0.659	(0.0064)	0.220	(0.0076)	0.449***	429
Czech Rep.	0.649	(0.0035)	0.213	(0.0045)	0.436***	1,320
Spain	0.615	(0.0023)	0.187	(0.0020)	0.429***	3,153
Belgium	0.622	(0.0059)	0.196	(0.0053)	0.426***	460
Austria	0.606	(0.0030)	0.190	(0.0023)	0.417***	1,599
Romania	0.694	(0.0041)	0.282	(0.0048)	0.411***	1,437
UK	0.598	(0.0032)	0.194	(0.0026)	0.405***	1,697
Poland	0.650	(0.0026)	0.260	(0.0029)	0.390***	2,492
Sweden	0.582	(0.0057)	0.203	(0.0018)	0.379***	512
The Netherlands	0.587	(0.0046)	0.210	(0.0017)	0.377***	607
Denmark	0.539	(0.0040)	0.170	(0.0012)	0.368***	813

Notes: Objective and Subjective Corruption show the mean of individual factor scores derived from the GSEM estimation and normalised between 0 and 1. Diff. performs the mean comparison test between the two means (subjective and objective corruption factor scores). Countries are ranked from the highest to the lowest corruption gap given by the difference in the factor scores. \*\*\* significance at 1%.

Table 6: The determinants of corruption

Subjective Corruption	Objective Corruption
<i>Indicators</i>	
Health Care	Police Force
Education Services	Education Services
Police Force	Health Care
<i>Correlation</i>	
Income Level	Age
Educational Level	Urban Area
Age	Mother Tongue
Urban Area	Gender
Mother Tongue	Income Level
Gender	Educational Level

Note: Additional controls for Country and Regions.

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