Estimating Corruption Around the World: An analysis by Partial Least Square - Structural Equation Modelling

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Abstract

This paper analyzes causes and consequences of corruption by a Structural Equation Model in order to estimate an index of perceived corruption (S-CPI) in 165 countries from 1995 to 2016. By approaching the corruption as a latent variable, the S-CPI is calculated by combining in an unified statistical framework, on the one hand, the existing indexes of perceived corruption and, on the other hand, the abundant economic literature on the determinants and consequences of corruption. The S-CPI provides (i) the most updated and widest coverage in terms of countries and time span of corruption around the Word; (ii) a novel comprehensive empirical analysis of the direct and indirect effects of the causes of corruption. The results have relevant policy implications to identify the most effective measures to fight corruption.

Keywords: Corruption; Partial Least Square; World Economy; Structural Equation Modelling.

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1. Introduction

While everyone has a clear idea of what corruption means (e.g. bribery, nepotism, misappropriation), identifying an exhaustive and universally accepted definition of it is not an easy task. Etymologically, the word "corruption" derives from the Latin verb *corrumpere* (cum–rumpere) and means "to break" "together". This etymology delineates the two main peculiarities of who is involved in a corruption act: it is an activity that breaks (legal or moral/ethical) norms and, this act necessarily involves at least two persons - the corruptor and a person entrusted with a position of authority -. The first difficulty to refer to legal or ethical norms to define a multifaceted phenomenon as corruption is that corruptive practices may be legal in many countries and these rules may change over time (e.g. laws on lobbying activities, financing of political parties). For that reason, in order to allow comparative analyses of corruption across countries, the most common definition of corruption in economic literature prevents a reference to legal or ethical norms but simply defines as corruption "*the abuse of public office for private gain*" (World Bank, 1997: 8).

Extensive scholarly research has pointed out the several effects of corruption on socio-economic systems. In particular, since the late 1990s, the empirical economic literature has exponentially[1] increased due to the raising quality and availability of data on (perceived) corruption. This literature highlights three main criticisms. The first one refers to the reliability of the indexes on (perceived) corruption utilized to describe the size of corruption activities. A recent critical viewpoint - reviewed in section 2 - raises significant doubts about whether the perceptions-based indicators are reliable proxies of actual corruption level. For instance, Treisman (2015) considers the differences in countries' perceived corruption score as for the most part correlated to national cultural stereotypes or to a wider media coverage, e.g. due to some corruption scandals, rather than the actual extent of corruption activities.

[1] For instance, by searching the word "corruption" in the titles of the documents indexed by Scopus database, there are about about 100 between 1988 and 1998; about 1400 in the period 1998-2007 and 4850 in the decade 2008-2017.

A second criticism refers to the common practice to treat "*corruption as unidimensional and as synonymous to bribery*" (Philp 2015: 19). According to Andersson (2017), other forms of corruption (e.g. favoritism, improper interference, interest conflicts) usually more common in developed countries are partially neglected by usual corruption perceived indexes that focus essentially on bribery. Accordingly, taking into account that the degree to which bribery can serve as a proxy for overall corruption varies depending on the nature of a political system and degree of economic development. Andersson (2017) concludes that, in established democracies with highly developed economies and low corruption, the accuracy of conventional perceived indexes[2] may be particularly poor.

The third criticism refers to the evidence that older and more recent studies on corruption often contradict each other. Accordingly, doubts rise about the reliability of the estimated corruption indexes due to statistical inconsistency. The predominant explanation to these conflicting findings points out as, at least partially, these discrepancies are a consequence of more sophisticated econometric approaches and/or larger data sets used in the recent analyses (Dimant and Tosato 2018).

From a methodological viewpoint, this research aims to contribute to this debate by focusing on the last two previous criticisms. In particular, in ordr to deal with the second criticism, we apply a statistical approach which considers corruption as a multidimensional phenomenon. As the third criticism concerns, we apply an estimation method - i.e. Partial Least Square estimation approach to Structural Equation Modelling (PLS-SEM) - which has two main advantages in comparison to the previous empirical analyses. First, it is able to translate in testable relationships the economic hypotheses on causes and consequences of corruption by means of a unified statistical approach – the so-called "structural model" of the SEM. The second pro of a SEM consists in approaching the (perceived) corruption as an unobservable variable (i.e. latent construct) that interacts in a complex way with several

[2] This deduction is based on analysis of Corruption Perceptions Index of Trasparency international and the Control of Corruption variable of World Bank in the Sweden context. Specifically, "*In such settings, bribery is more likely only the tip of the corruption iceberg, and undue influence and conflicts of interest are more frequent occurrences*." (Andersson 2017: 70).

other socio-economic unobservable (e.g. institutional variables) and observable variables. In this sense we improve reliability of the estimates of perceived corruption by reducing measurement errors.

To the best of our knowledge, this study is the first attempt to estimate an index of Perceived Corruption by PLS-SEM[3] - hereinafter *Structural Corruption Perception Index* (*S-CPI*) -.

Essentially, PLS-SEM is a system of interdependent equations estimated using both Factor Analysis and multiple regression techniques up to the model adequately converges by an iterative method.

From a positive viewpoint, the contribution of this research consists in providing an updated, wide range and comparable meta-index of perceived corruption to 165 countries using annual data over the period 1995 – 2016.

From a normative viewpoint, we will show both which are the main factors affecting corruption and the decomposition of the total effect of the causes on corruption in direct and indirect effects. These findings have important implications for policy makers.

The paper is organized as follows. The next section summarizes the reasons behind the criticism that the perceptions-based indicators may be misleading to proxy actual corruption. Section 2 explains the empirical approach. The third section shows the model specification by reviewing the economic reasons behind the inclusion of causes and consequences of corruption. Section 4 reports empirical results and discusses the findings. Section 5 concludes. Two online appendixes describe dataset and annual scores of *S-CPI* for all the 165 countries, respectively.

[3] Similart to this research, Dreher et al. (2007) estimate an index of perceived corruption by a structural equation modelling - however there are several differences in terms of: (1) estimation method - they estimate the model by a covariance-based approach while we apply a PLS approach; (2) model specification - they estimate corruption by a Multiple Indicators and Multiple Causes (MIMIC) model while we apply a wider structural model specification; (3) exhaustiveness of measurement and structural models - they define one latent variable (i.e. corruption) with 5 observable causes and 4 observable indicators while we define 23 latent variables and, for each of these constructs, we specify a distinct measurement model. It implies to use in our model 58 manifest variables; (4) extensiveness of corruption indexes - Dreher et al. (2007) estimate an index of corruption covers 100 countries over the period 1976-1997, our index covers 165 countries over the period 1995-2016.

2. What Do Corruption (Perception) Indices Measure?

A growing literature arises doubts on using perceptions data to capture differences in corruption across countries (Charron 2016). As a consequence, the common practice to use as data source for empirical analyses corruption perception indexes may be misleading because perception data are not reliable proxy of corruption experience (e.g. Andersson and Heywood 2009; Olken 2009; Melgar et al. 2010; Rose and Mishler 2010; Razafindrakoto and Roubaud 2010; Donchev and Ujhelyi 2014; Heywood and Rose 2014; Treisman 2015; Charron 2016; Ning 2016).

Melgar et al. (2010) criticize the use of perception indexes by analyzing how personal characteristics shape the individual's perception of corruption. On the basis of microdata evidence, they find, for instance, that: women are more likely to perceive a higher level of corruption than men; people who are married (or live as married) tend to perceive a lower level of corruption than other people; people who have completed, at least, secondary education are more likely to perceive a lower level of corruption; those who are working in a private enterprise are more likely to perceive a higher level of corruption than those who are employed in the public sector; self-employed people tend to perceive a higher level of corruption and, in general, the socio-economic status significantly affects the perception of corruption. In particular the author concludes that the individual's perception of corruption decreases with socio-economic status, so that "*the better-off people are materially and the higher their social standing, the more likely they are to view the world and other people in a favorable light"* (Melgar et al. 2010: 125). This analysis highlights how individual and social characteristics of the sample used to collect data on perception, play a relevant role in shaping corruption perception. As a consequence, cross-national differences in corruption perception indexes may be led by socio-demographical differences in the sample composition rather than differences in levels of actual corruption among countries.

Donchev and Ujhelyi (2014) observe that three of the most common corruption perception indexes used in literature[4] are biased measures of actual corruption. On the basis of the estimates of actual corruption activity based on the International Crime Victimization Survey and the World Business Environment Survey, they conclude that corruption perception is only weakly correlated to corruption experience in, at least, two cases. First, perceptions are sensitive to absolute levels of corruption (i.e. number of occurrences) rather than relative corruption levels (i.e. percentage of population affected). As a result cross-country comparisons of corruption levels, if based on perceptions, became problematic because perceptions will tend to be biased upward in larger countries. Second, corruption perception indexes exhibit diminishing sensitivity to corruption experience, thus, corruption perception indexes are worse proxies for actual corruption in highly-corrupted countries than in low-corrupted ones. In other terms, Donchev and Ujhelyi (2014) point out that, perceptions will tend to be biased downward in highly corrupted countries, which usually correspond to developing countries.

According to Treisman (2015: 96) the indexes of perceived corruption usually capture "*differences in countries' reputations, based in part on prevailing stereotypes and media coverage"* rather than the actual magnitude of corruption (e.g. amount of bribery or misappropriation). He states that experts and businessmen are themselves influenced by popular theories about what causes corruption. When asked how widespread corruption is in their country, they then rely on such theories, inferring that countries, where the government is authoritarian or media are perceived as not free, "must also be" corrupt. Treisman's hypothesis finds an indirect support on the psychological theory of cognitive dissonance.[5] People who live, or perceive to live, in a country with lower trust in Institutions may uncritically

[4] Precisely, the Corruption Perceptions Index published by the Transparency International; the Control of Corruption index published by World Bank and the Corruption index of the International Country Risk Guide.

[5] People seek psychological consistency between their personal expectations and the reality because internal inconsistency generates mental discomfort. It due to the evidence that individuals prefer to think of themselves as clever and are thus inclined to misperceive reality because it is psychologically less costly than admitting that they made a wrong choice. Accordingly, unconsciously, they tend to misperceive the reality to align their cognitions (pre-concept to live in a high or low corrupted corrupted country) with their effective life experience of real world.

overweigh information that confirms their beliefs (e.g. media news on corruption) while they over-critically reject disconfirming data.

Further support on the hypothesis that corruption perception is a weak predictor of corruption experience is pointed out by empirical analyses focused on specific geographical area. (e.g. Seligson 2006, for six Latin American countries; Olken 2009, for Indonesia; Rose and Mishler 2010, for Russia; Morris and Klesner 2010, for Mexico; Razafindrakoto and Roubaud 2010, for eight sub-Saharan African countries).

Although this growing literature against the use of perception index as proxy of corruption experience, a causal relationship between perceived corruption and individal behavior is clearly identifiable. According to the literature on the relationships among weak institutions, social stigma and individual behavior (e.g. Dell'Anno 2009), institutional distrust and higher perception of corruption may be considered two sides of the same coins. As a consequence, a high perception of corruption increases corruption experience, by reducing the expected cost to break legal and ethical rules at individual level.

In conclusion, while we could raise doubts that people accurately perceive the actual level of corruption - and so the estimated indexes of perceived corruption are biased - no doubts should arise when considering the measures of perceived corruption among the most important explanatory variable (i.e. predictors) of the real (unobserved) corruption.

3. The Economic theory behind the SEM model: Causes, Consequences and Indicators of Corruption

Duncan (1975: 149), describing the SEM, stated that "*the meaning of the latent variable depends completely on how correctly, precisely and comprehensively the causal and indicator variables correspond to the intended semantic content of the latent variable*", thus the reliability of the estimates of our key latent variable (i.e. corruption) depends completely on what causes and consequences are selected to specify the model. Accordingly, although a comprehensive state-of-the-art overview of

existing literature on the determinants of corruption is not an aim of this study[6], in the following, we describe the arguments behind the SEM specification used to estimate the *S-CPI* index.

Following the literature on corruption and data availability, we specify a model with 23 latent variables and 58 observed indicators.[7] In SEM terminology, the system of statistical relathionships explaining how latent variables (causes, consequences and indicators of perceived corruption) interact one to each other is defined as structural or "inner" model. The systems of equations - so-called "blocks" – in where each latent variable is connected to a sub-set of manifest variables constitute the measurement or "outer" model – in the SEM. In the following, we describe the structural model while and provide just indications on the observed variables included in the outer models. Greater details on definitions and sources of these 58 observed indicators are provided in the appendix A1.

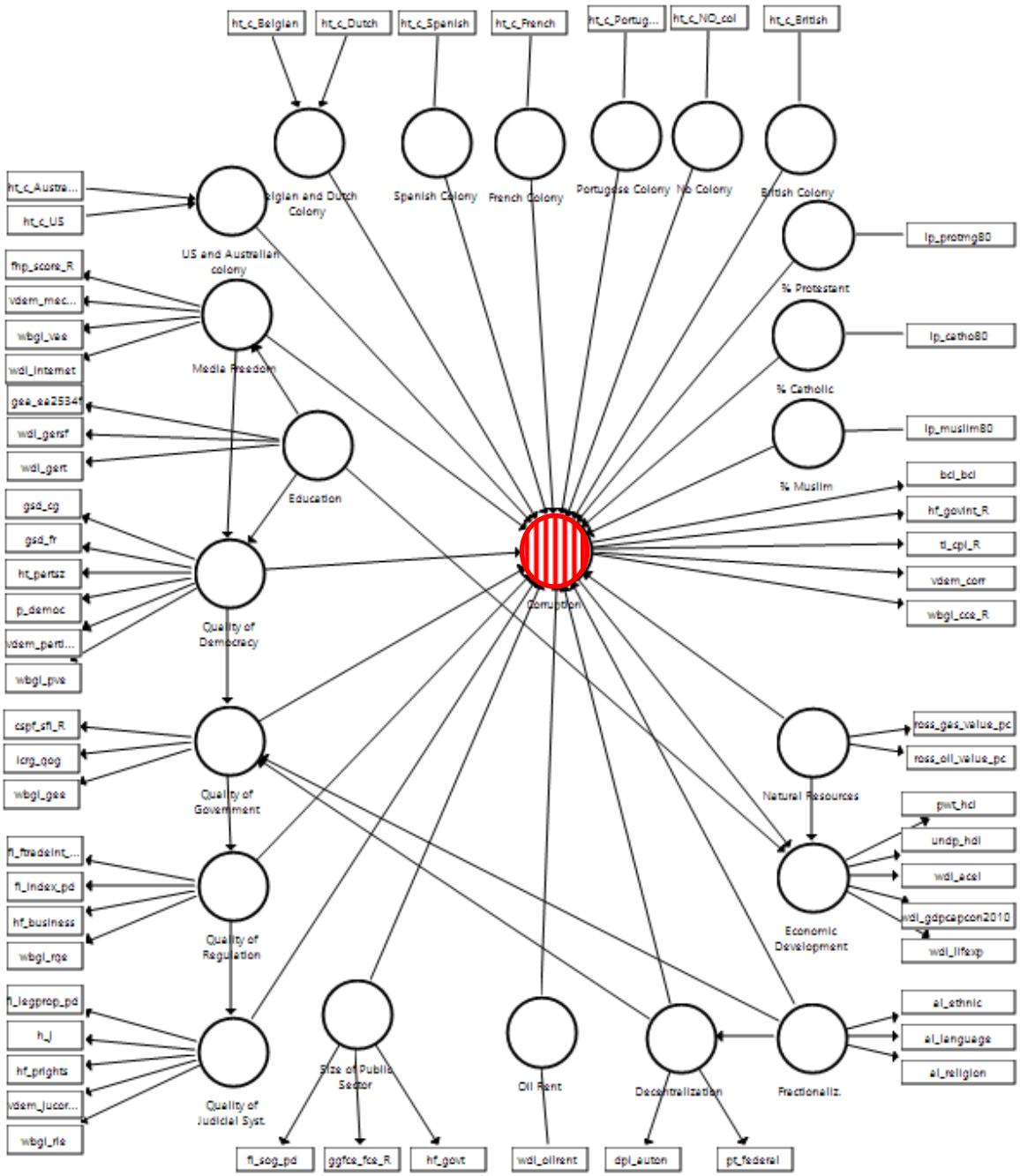
In SEM literature, it is usual to show the system of simultaneous equations in a unified framework, i.e. including both structural and measurement models, to draw a path diagram. This conventional graphical instrument consists of boxes (indicating manifest variables) and circles (representing latent variables), which are connected by arrows (indicating one-way causal relationship).

Figure 1 shows the widest SEM specification (model 1). The dataset used for this analysis is extracted by "*The Quality of Government Standard Dataset"* collected by Teorell et al. (2018). Specifically, we constraint the database to 165 countries over the period from 1995-2016 in order to balance presence of missing values with a sample size appropriate to investigate on the structural determinants of corruption. All variables are scaled to have zero mean and unit variance.

[6] In chronological order, we refer the reader to Ades and Di Tella (1997), Bardhan (1997), Tanzi (1998), Rose-Ackerman (1999), Jain (2001), Aidt (2003), Svensson (2005), Lambsdorff (2006, 2007), Seldadyo and de Haan (2006), Serra (2006), Treisman (2007, 2015), Goel and Nelson (2010), Enste and Heldman (2017), Dimant and Tosato (2018).

[7] For nine latent variables there is a single indicator with a loading coefficient equal to 1. It means that the latent variable is fixed equal to the corresponding single manifest indicator. This specification allows to keep distinct measurement from structural model as request to apply the PLS-SEM algorithm.

Figure 1: Path Diagram - Model 1



3.1 The measurement Model of S-CPI index

The latent variable "*Corruption*" (*S-CPI*) is measured by some of the most known cross-country indexes that account for the magnitude of perceived corruption as declared by panels of national experts and business people. Specifically the five indicators are: (a) The *Corruption Perceptions Index* published by

the Transparency International (*t_cpi_R*). The score of the original index – that is related to perceptions of the degree of corruption as seen by business people, risk analysts and the general public – is rescaled in order to get higher scores when the level of perceived of corruption increases; (b) The *Bayesian Corruption Indicator* estimated by Standaert (2015) (*bci_bci*). It is a composite index of the perceived overall level of corruption that combines the information of 20 different surveys and more than 80 different survey questions that cover the perceived level of corruption. (3) The *Political Corruption index* (*v-dem_corr*) is equal to the average of *public sector corruption index* as estimated by Coppedge et al. (2017) and Pemstein et al. (2017) in the "Varieties of Democracy (V-Dem)" Project. (4) The *Control of Corruption index* (*wbgi_cce_R*) is extracted by the Worldwide Governance Indicators database of the World Bank and measures perceptions of corruption. (5) The *Freedom from corruption* (*hf_govint_R*) is the (rescaled) index of *Freedom from corruption* published by the Heritage Foundation (2017).

3.2. The structural Model of S-CPI index: the causes of Corruption

Following the abundant research on causes and consequences of corruption[8] we specify the structural model of PLS-SEM. Specifically, each of the potential determinants of corruption is approached as a latent variable. This methodology allows to model not only the direct effects of the causes on corruption but also the interactions among them within the structural model. In particular, according to the unobservable and/or multidimensional nature of potential causes and consequences, we define the latent variables by "reflective" (i.e. by applying a factor model) or a "formative" (i.e. by defining the latent construct as a linear combination of the manifest variables in the outer model) measurement model.

3.2.1 Institutional Causes of Corruption

The quality of the institutional context is unambiguously considered by literature as one of the most important determinant of corruption. These studies found that in countries where citizens perceive the

[8] See Enste and Heldman (2017), Dimant and Tosato (2018) for recent discussion on this literature.

regulatory action of their government as effective, the Judicial System as impartial and the level of trust in political institutions as adequate, the perception of corruption is generally low.

However, this strand of empirical literature faces objective difficulty to test the relevance of institutions on corruption due to: measurement errors in measuring these variables; the multidimensional nature and unintelligibility of the concept of "institution"; the probability of occuring in spurious correlations and multicollinearity among institutional variables. On this issue of statistical difficulties to test the relationship between institutions and corruption, Treisman (2015) states that, as a consequence of the effects of institutional quality on other potential causes of corruption, the empirical findings may generate misleading inference. Taking into account this criticism, we opt for a structural equation approach because, in comparison to the multiple regression approach, it is able to effectively control for the multicollinearity among the causes of corruption. In particular, SEM allows to model the collinearity among the latent variables (i.e. causes and consequences) within the structural model.

Taking into account the predominant literature and data availability, we separate the quality of "institutional context" in four main dimensions of quality: "*Quality of Government*" (*Q_Gov*); "*Quality of Judicial System*" (*Q_JudS*); "*Quality of Regulation*" (*Q_Reg*) and "*Quality of Democracy*" (*Q_Dem*). In the following subsections, for each of these latent determinants of corruption, we define a reflective measurement model to take into consideration different potential indicators of each latent variable.

3.2.1.1 Institutional Cause: Quality of Government

The "*Q_Gov" i*s measured by the three most known indexes used in empirical literature to account the quality of government. These are: the "*ICRG Indicator of Quality of Government*" (*icrg_qog*) included in the International Country Risk Guide indicators and produced by the PRS Group et al. (2018); the (rescaled) index of "*State fragility"* (*cspf_sfi_R*) *index* calculated by Marshall and Elzinga-Marshall (2017) and the index of "*Government Effectiveness*" extracted by the Worldwide Governance Indicators (*wbgi_gee*).

3.2.1.2 Institutional Cause: Quality of Judicial System

The "*Q_JudS"* has two complementary effects on corruption. On the one hand, a good judicial system enhances the citizens' perceived of fairness and legality, therefore, it potentially increases psychological and reputational cost, i.e. via social stigma, to be involved in corruption activity. On the other hand, a high-quality judicial system increases the monetary cost to be corrupted because, a more effective law enforcement augments the threat of punishment and the corresponding sanction. Accordingly, we expect that the higher the quality of the judicial system, the stronger the deterrent to engage in corrupt behavior and, in turn, the lower is the level of abuse of public office for private gain.

We include five indicators to take into account several aspects of the judicial system: the independence of the judiciary; the degree to which governments protect private property rights; the integrity of the legal system; the extent to which agents have confidence in and abide by the rules of society; etc. These manifest indicators are extracted by: Gwartney et al. (2016) (*fi_legprop_pd)*; Henisz (2002) (*h_j*); Heritage Foundation (2017) *(hf_prights)*; Coppedge et al. (2017) and Pemstein et al. (2017) (*vdem_jucorrdc)*; Worldwide Governance Indicators database (*wbgi_rle*).

3.2.1.3 Institutional Cause: Quality of Regulation

The "*Q_Reg"* latent construct is measured by two groups of indicators that account for different forms of regulations that are considered potential determinants of corruption in literature.

The first type of regulation is based on Tanzi's (1998) hypothesis that every rule that gives a kind of monopoly power to the officials can be a potential source of abuse of discretionary power. Similarly, Dimant and Tosato (2018) conclude their survey on the effect of regulation on corruption by stating that more regulations, by intensifying the frequency of interactions between public officials and private operators, increase the likelihood of corrupt behaviors. According to this literature, we include two indexes of general regulation burden which measure the degree to which the policies and institutions of countries are supportive of economic freedom. In particular, we use the "*Index of Economic Freedom of the World*" (*fi_index_pd*) which measures the degree to which the policies and institutions of countries are supportive of economic freedom (Gwartney et al. 2016) and the "*Business Freedom*" index

(*hf_business*) that includes 10 components based on objective data from the World Bank's Doing Business study and is published by Heritage Foundation (2017).

The second type of regulation refers to administrative and fiscal rules that reduce openness to international trade. Abundant empirical evidence supports the hypothesis that greater levels of openness and trade, or integration in the world economy have a significant effect in reducing corruption. The basic rationale is that trade integration improves the political and economic structure of the country and reduces rent-seeking activities. The quality of this kind of regulation that controls the openness to international trade is accounted by the "*Freedom to Trade Internationally*" (*fi_ftradeint_pd*) calculated by Gwartney et al. (2016). This index is a linear combination of five sub-indexes as Taxes on international trade, Regulatory trade barriers, Actual size of trade sector compared to expected size, The difference between the official exchange rate and the black market rate, International capital market controls.

Finally, the "*Regulatory Quality*" index - extracted by the Worldwide Governance Indicators (*wbgi_rqe*) – is able to account both general and international trade organization because it measures the incidence of market unfriendly policies perceptions of the burdens imposed by excessive regulation both in areas of foreign trade and business development.

3.2.1.4 Institutional Cause: Quality of Democracy.

The "*Q_Dem*" is, among the institutional causes, the one with a more complex and multidimensional nature. Two opposite hypotheses rationalize the statistical relationship between democracy and corruption. The predominant literature (e.g. Sandholtz and Koetzle 2000, Treisman 2000, Kunicova and Rose-Ackerman 2005) considers the lack of democracy as a determinant of corruption because the electoral competition represents a primary source of accountability for public officials (i.e. politicians). Democratic systems have in effect more incentives than authoritarianisms to discover and punish corrupted politicians: elections increase the probability that corrupt officials will be exposed and removed from office, the opposition has an incentive to discover corrupt activities by the incumbent and voters have an interest in not reelecting politicians who favor their own private interests over those of

the electorate (Kolstad and Wiig 2015). Pellegata (2012) points out that in democracy, politicians have fewer incentives to accept bribes because their position is not guaranteed in the way that it is in non-democracies.

An alternative hypothesis assumes that corruption may also increase with the electoral competition because election campaigns require funds, therefore make political parties and candidates vulnerable to rent-seekers and lobbyists (e.g. Rose-Ackerman 1999).

Although the prevalent empirical literature supports the first hypothesis (i.e. better democracy, lower corruption) some empirical studies find ambiguous result. For instance, Treisman (2007) estimates a significantly negative relation between democracy and corruption, but he notes that the result is sensitive to the democracy index used in estimations.

We attempt to measure the "quality of democracy" by means of multiple observable proxies of the quality of political system and functioning of electoral competition. These manifest indicators account for the competitiveness of political participation, the openness and competitiveness of executive recruitment, the access to civil and social rights and the political stability. Accordingly, the reflective measurement model of this latent variable includes six indicators. (a) The index *"Checks on Government"* (*gsd_cg*) is based on three sub-attributes: effective parliament, judicial independence and media Integrity. (b) The index of "*Fundamental Rights*" (*gsd_fr*) is a composite index of three sub-attributes: access to justice, civil liberties, and social rights and equality -. Both these two indexes are estimated by the International Institute for Democracy and Electoral Assistance (2017). (c) The "*Size of Largest Party in Legislature*" (*ht_partsz*) counts the number of seats of the largest party divided by the total number of seats in the legislative assemblies and it is based on Wahman et al. (2013) and Hadenius and Teorell (2007). (d) The index of "*Institutionalized Democracy*" (*p_democ*) is composed of four sub-attributes: the competitiveness of political participation, the openness and competitiveness of executive recruitment, and constraints on the chief executive. It is estimated by Marshall et al. (2017). (e) The "*Participatory democracy index*" is based on the answers to the question: "To what extent is the ideal of participatory democracy achieved?" as collected by the Varieties of Democracy (V-Dem) Project published by Coppedge et al. (2017) and Pemstein et al. (2017). (f) The "*Political Stability and Absence*

of Violence/Terrorism" (*vdem_partipdem*) retrieved by the Worldwide Governance Indicators. This index measures perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism.

3.2.2 Cause: Size of public sector

The size of the public sector (*Size_PubS*) is considered as a potential determinant of corruption because misuse and extent of public power are expected to be positively correlated (Goel and Nelson 1998; Lambsdorff 2006; Arvate et al. 2010). However, Dimant and Tosato (2018) show as this correlation between the size of government activities and corruption is not so evident in empirical literature. For instance, some studies conclude that larger governments reduce corruption (e.g. Goel and Budak 2006; Goel and Nelson 2010). In an attempt to explain these ambiguous results, Kotera et al. (2012) find evidence that, for OECD and Latin American Countries, this effect depends on the quality of democracy levels. In particular, they conclude that the size of the government sector increases corruption when there are low levels of democracy and it decreases corruption when there are high levels of democracy.

In our SEM specification, this latent construct is measured by three manifest variables: the "*Size of Government: Expenditures, Taxes and Enterprises*" index (*fi_sog_pd*) published by Fraser Institute (Gwartney et al. 2016); the "*Freedom from government"* factor (*hf_govt*) published by Heritage Foundation (2017). This index is based on two components: Government expenditure as a percentage of GDP, Revenues generated by state-owned enterprises and property as a percentage of total government revenue; the "*Share of Non-Government Final Consumption Expenditure*" (*ggfce_fce_R*) obtained by rescaling the ratio between the General Government Final Consumption Expenditure and Final Consumption Expenditure published by United Nations Statistics Division (2017).

3.2.3 Cause: Decentralization

Similarly to the "*Size_PubS*", also the inclusion of a latent variable to account the degree of decentralization (*Decent)* among the determinant of corruption is not supported by clear empirical evidence because studies reach conflicting findings. On the one hand, some researches find that higher

degree of decentralization is associated with lower levels of corruption (e.g. Shleifer and Vishny 1993, Fisman and Gatti 2002, Arikan 2004, Lessmann and Markwardt 2010, Dell'Anno and Teobaldelli 2015). The prevailing rationale is that greater decentralization enables better monitoring and lower corrupt activities. By the same token, Dimant and Tosato (2018: 338) state that decentralization should reduce corruption because it intensifies competition among jurisdictions "*...mitigates government-induced distortions, and give individuals the option of changing district rather than engaging in corrupt practices*". On the other hand, other studies conclude that decentralized countries and federal government show higher levels of corruption (Treisman 2000, 2006; Fan et al. 2009). The rationale behind this result is based on the intuition that more red tape generates greater opportunities to engage in corrupt activities.

In our model, decentralization is measured by two dichotomic indicators: the "*Federal Political Structure*" (*pt_federal)* - that accounts if a country has a federal political structure (Persson and Tabellini 2003) - and an index labelled as "*Autonomous Regions*" (*dpi_auton*), extracted by the *Database of Political Institutions* as updated by Cesi Cruz and Scartascini (2016). These binary indicators take on a value of 1, if in the country there are regions constitutionally designated as "Federal", "autonomous", "independent" or "special".

3.2.4 Cause: Media Freedom

High levels of media access and independent press (*Media_Fr)* have been documented to reduce corruption.[9] The reasons are straightforward: a high quality and uncensored press sheds light on abuse of public power and increases the potential social cost of being publically discredited for corrupt behavior (Dimant and Tosato 2018). Enste and Heldman (2017) point out that, also by using different indicators to account for freedom and access to the press[10], the hypothesis that a freer press is connected to lower

[9] See Brunetti and Weder (2003) and Kalenborn and Lessmann (2013) for an overview.

[10] Pellegrini (2011) uses the newspaper circulation; Ahrend (2002), Brunetti and Weder (2003) and Lederman et al. (2005) utilize the index of press freedom provided by the Freedom House; Vaidya (2005) uses previously unexplored data on various sub-components of press freedom.

corruption levels is robust. Following these analyses, we specify the Structural model of the SEM in order to test both direct and indirect impact of "*Media_Fr*" on perceived corruption (i.e. via "*Q_dem*")[11]. As the reflective measurement model of the latent variable "*Media Freedom*" concerns, we employ four indicators: (1) the "*Media corrupt*" index (*vdem_mecorrpt*) provided by Coppedge et al. (2017) and Pemstein et al. (2017). This manifest variable accounts to the opinion of interviewees about the possibility that journalists, publishers, or broadcasters accept payments in exchange for altering news coverage. It is based on the questions included in the Varieties of Democracy (V-Dem) Project; (2) the meta-index of "*Voice and Accountability*" published by World Bank in the Worldwide Governance Indicators (*wbgi_vae*). It includes sub-indicators measuring the independence of the media; (3) the "*Press freedom index*" (*fhp_score_R*) provided by the Freedom House (2018). It is the most used indicator in this literature and includes four factors that may affect the freedom of the press in a country (i.e. Laws and regulations, Political pressures and controls, Economic Influences and Repressive actions); (4) The percentage of individuals who have used the internet in the last 3 months on the total population (*wdi_internet*) extracted by the *World Development Indicators* (WDI).

3.2.5 Cause: Fractalization

Mauro (1995) was one of the first scholars who pointed out as more ethnically fractionalized countries tend to be more corrupted. Pellegrini and Gerlagh (2008) propose two rationalizations for this in-group favoritism. On the one hand, civil servants and politicians would exploit their positions to favor members of their own ethnic group. On the other hand, fractionalized societies tend to under-provide public goods, this would increase the dependency on some groups to obtain essential services from the State and, in turn, it expand patronage system. Treisman (2000) argues that ethnical fractionalization may promote corruption since corrupt officials could be protected by their own ethnic groups for political reasons. Analogously, Dimant and Tosato (2018) state that if members of one ethnicity are elected expressly because considered as representatives of that ethnic group, they are more likely to

[11] Brunetti and Weder (2003) and Kalenborn and Lessmann (2013) conclude that quality of democracy and freedom of the press are two strictly connected causes of corruption. Our analysis empirically confirms this hypothesis.

maintain that position even if they display a corrupt behavior related to favoritism of their ethnic group who will reciprocate by helping them to keep in office.

In our model, we specify a reflective measurement model that includes the three main sources of fractionalization: the "*Ethnic Fractionalization"* (*al_ethnic*) – where the definition of ethnicity involves a combination of racial and linguistic characteristics - ; the "*Language Fractionalization*" (*al_language*) and "*Religion Fractionalization*" (*al_religion)*. These manifest indicators are extracted by Alesina et al. (2003), the higher the number, the more fractionalized the society is.

3.2.6 Cause: Endowment of natural resources

In presence of natural resource abundance, governments become less efficient, since citizens and officials compete for rents and invest less in other forms of capital, such as human capital (Enste and Heldman 2017). This theory finds support in several empirical studies: Ades and Di Tella (1999); Leite and Weidemann (1999); Montinola and Jackman (2002); Bhattacharyya and Hodler (2010); Busse and Gröning (2013).

Busse and Gröning (2013) summarize the three main causal mechanisms through which natural resources could have an impact on corruption. The common denominator of these explanations is that with abundant natural resources, the government collects large revenues from resource extraction, therefore, the first reason behind the positive correlation between natural resource and corruption is that the abundance of rents reduce the need for the government to tax the population, low-taxed citizens demand less accountability of the government and, in turn, lowering the pressure to improve institutional quality (Ross 2001). The second mechanism hypothesizes that government can spend these revenues to strengthen national security, that impede popular rebellions for more democracy or better institutions and government services (Clark 1997). The third mechanism assumes that resource-dependent governments may delay the modernization of the economic structure of the economy, since a large manufacturing sector would create alternative sources of economic and political power (Auty 2001; Ross 2001). In particular, governments with large revenues from natural resource exploiting may spend less on education, as resource sector requires only a few workers with sophisticated skills that can

be acquired abroad (Isham et al. 2005). Lower levels of education may then decrease the demand for institutional reforms.

As Busse and Gröning (2013) summing up, these causal mechanisms explain because in resource-abundant countries the institutional setting and quality of governance may be lesser than resource-poor countries. This latent variable (*Nat_Res*) is measured by two indicators: the "*Gas production value in 2000 $ per capita"* (*ross_gas_val*) and the "*Oil production value in 2000 $ per capita*" (*ross_oil_val*). These two variables are calculated dividing the total national value of gas or oil production, as extracted by Ross and Mahdavi (2015), by the country's population.

3.2.7 Cause: Oil Rent

The first two Busse and Gröning's (2013) causal mechanisms to explain why an abundance of natural resources may increase corruption are connected to the large size of rent usually associated to the mineral resource exploitation. Accordingly, we include a second latent variable to specifically account for the so-called "resource-curse" hypothesis among the determinants of corruption. La Porta et al. (1999) and Ades and Di Tella (1999) find that the rent generated by natural resource exploitation increases the corruption as a consequence of larger rent-seeking activities. On this strand of literature, Bhattacharyya and Hodler (2010) focus on the interactions between democracy and rent abundance, they show that high rents from natural resources increase corruption but only if democratic institutions are weak.

In the SEM specification the latent variable "*Oil_Rent"* is defined by a single indicator (*wdi_oilrent*), in this case, the latent variable becomes identical with the indicator [12]. This index is calculated by the *WDI* as the difference between the value of crude oil production at world prices and the total costs of production divided by the GDP.

3.2.8 Cause: Religion belonging

[12] PLS-SEM will assign an outer weight of 1 to that indicator, and the value of the latent variable is the normalized value (zero mean and unit variance) of the manifest variable.

La Porta et al. (1997) was among the first researches that include religion belonging as a potential "cultural" determinant of corruption. They argue that hierarchical religions (e.g. Catholicism, Eastern Orthodox and the Muslim religion) discourage the formation of horizontal trust and civic participation which, in turn, increase corruption. In this sense, these hierarchical religions have lower acceptance of abuse of power than and non-hierarchical religions (e.g. Protestantism). A number of scholars find empirical support to La Porta et al. (1997) hypothesis (e.g. Treisman 2000; Serra 2006; Paldam 2001; North et al., 2013). In contrast to these studies, Sandholtz and Gray (2003) show that Protestantism became statistically non significant both in larger samples, and when one controls for a variety of indicators on openness. For an overview on the empirical literature about relevance of religion on corruption see Landelorff (2006) and Dimant and Tosato (2018).

In our econometric model, we include three latent constructs in which each latent variable is defined by an outer model with one single manifest variable. Accordingly, we test the effect of the percentage of population belonging to the "Catholic" (*lp_catho80*), "Muslim" (*lp_muslim80*) or "Protestant" (*lp_protmg80)* religion in 1980 on perceived corruption. The source of data is La Porta et al. (1999).

3.2.9 Cause: Colonial Heritage

Theoretically, two hypotheses are proposed to rationalize the potential effect of colonial heritage on corruption. The first motivation focuses on colonial heritage as a proxy of institutional context. The citizens' attitude towards the State depends on the cultural and historical origins of society and their institutions. Consequently, considering the level of trust between citizens and government as a relevant determinant of corruption, the literature aims to account this factor by using data on colonial dominance as an explanatory exogenous cause of corruption.

A second motivation focuses on the nature of the Law legal system. For Treisman (2000) and Goel and Nelson (2010) the statistical differences between coefficients of religion between British and other colonial dominances may be due to the fact that Britain, and its former colonies, introduced the Common Law legal system. For the authors the Common Law system may be associated to superior

quality of government and regulation rather than the Civil Law system diffuse, for instance, in Latin countries.

However, empirical evidence on the effect of colonialism on corruption is mixed (Lambsdorff 2006, Enste and Heldman 2017). Treisman (2000) and Swamy et al. (2001) find that former British colonies tend to be perceived as less corrupt than countries with a different legal and political tradition. Serra (2006) finds that the effect of colonial heritage is significant, but only the British heritage showing a negative impact.

To account colonial heritage in our SEM model, we use a tenfold classification of the former colonial ruler of the country extracted by Wahman et al. (2013) and Hadenius and Teorell (2007). Specifically, we define seven latent variables - one for each European empire - with two aggregations (i.e. US with Australian colonies and Dutch with Belgian colonies) motivated by sake of parsimonious specification. In particular, all the countries are classified according to their colonial heritage as "Never colonized", "Spanish Colony", "British Colony", "French Colony", "Portuguese Colony", "US or Australian Colony" and "Dutch or Belgian Colonies", and we omit "Italian colony" as reference dummy variable.

3.3 Only Indirect Cause: Education

In theory, individuals with higher levels of education tend to be more committed to civil liberties and less tolerant of government repression and abuse of power (Truex 2011). Accordingly, there is not a direct effect of education on corruption but only a potential (indirect) effect of education via other latent constructs. In other words, we assume that more educated people promoting "*Media freedom*" and improving "*Quality of Democracy*" and in turn also the other institutional variables, may reduce corruption. In our model, "*Edu*" is measured by three indicators: the average years of educational attainment for women in the age group 25-34 (*gea_ea2534f*; Source: Institute for Health Metrics and Evaluation, 2015); the female enrollment in secondary education expressed as a percentage of the female population of official secondary education age *(wdi_gersf*; Source: *WDI)*; the total enrollment in tertiary education, expressed as a percentage of the total population of the five-year age group following on from secondary school leaving (*wdi_gert*; Source: *WDI*).

3.4 Consequences of Corruption: Socio-Economic Development

Although empirical analyses differ on the quantification of the economic and social costs of corruption, the economic research unambiguously reaches the conclusion that corruption is detrimental for socio-economic progress. The literature has identified several channels by means corruption constitutes a deadweight loss for society and slows down economic development. Among these, the most common are the reduction of tax and regulation compliance, the deterioration of social capital, the proliferation of rent-seeking activities, the obstacles for development due to imperfect market competition.

In order to account for different aspects of human, economic and technological development, we define in the SEM a latent variable – labelled as "*Socio-Economic development*" (*Econ_dev)* – by a block of five manifest variables: (1) the *Human Capital Index* (*pwt_hci*) which is based on years of schooling; (2) the *Human Development Index* (*undp_hdi*) is a summary measure of average achievements in three dimensions of human development (i.e. health, education and standard of living) extracted by the United Nations Development Program (2017); (3) the *Percentage of population with access to electricity* (*wdi_acel*). This index accounts for technological development and it is based on electrification data collected from industry, national surveys and international sources provided by *WDI*; (4) the *GDP per capita* (*wdi_gdpcapcon2010*) is gross domestic product at constant 2010 US dollar divided by midyear national population extracted by the *WDI*. (5) Lastly, the index of *Life expectancy at birth* (*wdi_lifexp*) extracted by the WDI. This index counts the number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life.

4. The Statistical approach: Partial Least Squares - Structural Equation Modeling

The SEM is a multivariate statistical approach that subsumes a whole range of standard multivariate analysis methods, including regression and factor analysis. It enables the researcher to simultaneously estimate complex causal relationships among latent (unobservable) and manifest (observable) variables. SEM is extensively applied in different fields such as business, marketing, management, psychological,

chemiometrics, social and, more recently, in macroeconomic research (e.g. Dell'Anno 2007; Dreher et al. 2007; Ruge 2010; Dell'Anno and Dollery 2014; Buehn et al. 2018).

There are two approaches to estimate a SEM: the Covariance-Based approach (CB-SEM) and the Partial Least Squares (PLS-SEM).[13]

In the CB-SEM, the parameters are obtained by minimizing iteratively the difference between the matrixes of sample covariance and predicted covariance. The usual minimization approach is based on the maximum likelihood (ML) function, therefore it relies on assumptions for predictor including specific joint multivariate distribution (multivariate normality in the case of ML function) and the independence of observations (Chin 1998). CB-SEM is the preferred approach for confirming or rejecting theories through testing of hypotheses, particularly when the sample size is large, the data is normally distributed, and most importantly, the model is correctly specified (Gye-Soo 2016).

The PLS-SEM applies to the same class of models as CB-SEM but the explained variance of the endogenous latent variables is maximized by estimating partial model relationships in an iterative sequence of ordinary least squares regressions (Hair et al. 2011).

This difference between CB-SEM and PLS-SEM estimation methods of SEM parameters mainly turns out in different characteristics and objectives (Richter et al. 2016). According to Faizan et al. (2018), the PLS-SEM is particularly promising when both the assumption of multinormal distribution is violated and the theory to explain the phenomenon requires to model complex interactions with many latent constructs. In this case the CB-SEM often encounters convergence problems (Hair et al. 2017; Rigdon 2016). For Esposito Vinzi et al. (2010b), PLS-SEM has the advantage, compared to the CB-SEM, that no strong assumptions, with respect to the distributions, the sample size and the measurement scale, are required. However, these advantages must be considered in light of some disadvantages. For example, the absence of any distributional assumptions implies that scholars cannot rely on the classic parametric inferential framework. (Chin 1998, Tenenhaus et al. 2005). PLS-SEM in fact applies the jackknife and

[13] Extensive reviews on the PLS approach to SEM are given in Chin (1998); Tenenhaus et al. (2005); Esposito Vinzi et al. (2010a); Hair et al. (2016, 2017); Faizan et al. (2018).

bootstrap resampling methods to derive empirical confidence intervals and testing hypotheses on statistical coefficients. For this reason "*the emphasis* (of the PLS) *is more on the accuracy of predictions than on the accuracy of estimation*."(Esposito Vinzi et al., 2010b: 52). Similarly, Shmueli et al. (2016) state that PLS-SEM, focusing on the explanation of variances rather than covariances, makes it a prediction-oriented approach to SEM. Another drawback is that the absence of a global optimization criterion in PLS-SEM implies a lack of measures for an overall model fit. This issue limits PLS-SEM's usefulness for theory testing and for comparing alternative model structures (Hair et al. 2012).

Taking into account that: (a) the main objective of this research is to predict an index of perceived corruption; (b) the network of relationships among corruption and its potential economic, cultural, and institutional determinants is complex; (c) the availability of several alternative indicators to measure variables that are intrinsically unobservable and/or multidimensional; (d) the violation of multivariate normality assumption; thus, we consider the PLS approach as preferable to CB method to estimate the proposed SEM.

Following Esposito Vinzi et al. (2010b) to formalize of PLS-SEM, the *inner* (or *structural* by using a CB-SEM jargon) model specifies the relation among latent variables, both endogenous and exogenous. In formal terms, the relationships among latent variables are represented by "inner weights" as following:

$$\eta_j = \beta_{0j} + \sum_{\forall q \neq j} \beta_{qj}\eta_q + \sum_{k=1,\ldots,K} \gamma_{kj}\xi_k + \zeta_j \qquad (1)$$

Where: η_j is the generic endogenous latent variable (with j = 1,…, J); β_{qj} is the path-coefficient interrelating the *q-th* endogenous latent variable to the *j-th* endogenous one; γ_{kj} is the path-coefficient interrelating the *q-th* exogenous latent variable to the *j-th* endogenous one, and ζ_j is the error in the inner relation (i.e. disturbance term in the prediction of the *j-th* endogenous latent variable from its explanatory latent variables).

The *outer* (or *measurement* in CB-SEM jargon) model describes the relations between latent and manifest variables.[14] Two types of outer models exist:

a) The *reflective measurement model,* in which manifest variables "reflect" latent variable. In this case the measurement model reproduces the factor analysis model, in which each variable is a function of the underlying factor (Esposito Vinzi et al. 2010b). Formally, each manifest variable is related to the corresponding (endogenous or exogenous) latent variable by a simple regression model:

$$x_{pq} = \lambda_{p0} + \lambda_{pq}\eta_q + \varepsilon_{pq}\,; \qquad x_{pk} = \lambda_{p0} + \lambda_{pk}\xi_k + \varepsilon_{pk} \tag{2}$$

Where λ_{pq} (λ_{pk}) is the loading associated to the *p-th* manifest variable in the *q-th* block of endogenous (*k-th* block of exogenous) latent variable and the error term ε_{pq} (ε_{pk}) indicates the measurement error. The underlying assumption of *reflective* measurement model is that the error has zero mean and is uncorrelated with the latent variable of the same block, i.e. for exogenous latent variable $E\left(x_{pq}\middle|\eta_q\right) = \lambda_{p0} + \lambda_{pq}\eta_q$ and for endogenous latent variable $E\left(x_{pk}\middle|\xi_k\right) = \lambda_{p0} + \lambda_{pk}\xi_k$.

b) The *formative measurement model*, in which manifest variables "constitute" latent variable. In this case the latent (endogenous or exogenous) construct is defined as a linear combination of the corresponding manifest variables, in formal terms:

$$\eta_q = \sum_{p=1}^{P_q} w_{pq}x_{pq} + \delta_q\,; \quad \xi_k = \sum_{p=1}^{P_k} w_{pk}x_{pk} + \delta_k \tag{3}$$

where w_{pq} (w_{pk}) is the coefficient linking each manifest indicators to the endogenous (exogenous) latent variable in the *q-th* (*k-th*) block – the so-called "outer weight"- ; P_q (P_k) is the number of manifest variables in the *q-th* (*k-th*) block; δ_q (δ_k) measures the fraction of the corresponding endogenous (exogenous) latent variable not accounted for by the block of indicators. The underlying assumption for the *formative* measurement model is that the error δ_q (δ_k) has zero mean and it is

[14] All manifest variables are scaled to have zero mean and unit variance.

uncorrelated with the manifest variables of the same block, i.e. $E\left(\eta_q \middle| x_{pq}\right) = \sum_{p=1}^{P_q} w_{pq} x_{pq}$ and

$E\left(\xi_k \middle| x_{pk}\right) = \sum_{p=1}^{P_k} w_{pk} x_{pk}$.

In this formalization, the PLS-SEM permits to estimate the outer weights ($w_{p\bullet}$) and the latent variable scores ($\hat{\eta}_j$ and $\hat{\hat{\xi}}_j$) by an iterative procedure. The estimation approach is named "partial" since it solves blocks one at a time by means of alternating single and multiple linear regressions. Once the convergence is achieved, for each block, the standardized latent variable scores are computed as weighted aggregates of manifest variables ($\hat{\eta}_q \propto \pm X_q w_q$)[15]. The inner weights (β_{qj}) are estimated afterwards by means of a regular regression between the estimated latent variable scores in accordance with the specified network of structural relations (Esposito Vinzi et al. 2010b). In particular, for each endogenous latent variable (η_j), the vector of inner weights (β_{qj}) is estimated by means of OLS regression as: $\beta_j = \left(\hat{N}'\hat{N}\right)^{-1} \hat{N}'\hat{\eta}_j$ where $\hat{N}$ includes the scores of the latent variables that explain the *j-th* endogenous latent variable η_j , and $\hat{\eta}_j$ is the latent variable score of the *j-th* endogenous latent variable.

4.1 The PLS-SEM models to estimate the Structural –Corruption Perception Index

In this section, we provide a formal representation of the PLS-SEM based on the literature exposed in the section 3. The widest PLS-SEM specification (Model 1), is described by the system of equations (4), and reproduces the path-diagram of Figure 1 in formal terms. For the sake of simplicity of the notation, we use the same symbols for exogenous and endogenous latent variables as well as their associate path coefficients. Accordingly, differently from equation (1), we label all the latent constructs as "endogenous" variables and, in turn, path-coefficients and errors are indicated by β and ζ, respectively:

[15] The symbol $\propto$ means that the left side of the equation corresponds to the standardized right side and the $\pm$ sign shows the sign ambiguity. This ambiguity is usually solved by choosing the signs of the weights for a whole block in order to make them coherent with the definition of the latent variable (Esposito Vinzi et al. 2010b).

$$
\begin{cases}
S\text{-}CPI_{it} = \beta_{21} Media\_Fr_{it} + \beta_{31} Q\_Dem_{it} + \beta_{41} Q\_Gov_{it} + \beta_{51} Q\_Reg_{it} + \beta_{61} Q\_JudS_{it} + \beta_{71} Size\_PubS_{it} + \\
\quad + \beta_{81} Fract_{it} + \beta_{9,1} Nat\_Res_{it} + \beta_{10,1} Oil\_Rent_{it} + \beta_{11,1} Decent_{it} + \beta_{12,1} NeverC_{it} + \beta_{13,1} FrenchC_{it} + \\
\quad + \beta_{14,1} SpanC_{it} + \beta_{15,1} US\&AustrlC_{it} + \beta_{16,1} PortugC_{it} + \beta_{17,1} Bel\&DutC_{it} + \beta_{18,1} BritishC_{it} + \\
\quad + \beta_{19,1} \%Cath_{it} + \beta_{20,1} \% Musl_{it} + \beta_{21,1} \%Protest_{it} + \zeta_{1,it} \\
Media\_Fr_{it} = \beta_{22,2} Edu_{it} + \zeta_{2,it} \\
Q\_Dem_{it} = \beta_{23} Media\_Fr_{it} + \beta_{22,3} Edu_{it} + \zeta_{3,it} \\
Q\_Gov_{it} = \beta_{34} Q\_Dem_{it} + \beta_{94} Fract_{it} + \beta_{12,4} Decent_{it} + \zeta_{4,it} \\
Q\_Reg_{it} = \beta_{45} Q\_Gov_{it} + \zeta_{5,it} \\
Q\_JudS_{it} = \beta_{56} Q\_Reg_{it} + \zeta_{6,it} \\
Decent_{it} = \beta_{9,12} Fract_{it} + \zeta_{12,it} \\
Econ\_Dev = \beta_{1,23} S\text{-}CPI_{it} + \beta_{22,23} Edu_{it} + \beta_{9,23} Nat\_Res_{it} + \zeta_{23,it}
\end{cases}
\qquad (4)
$$

Where the subscript *i=1,…, 165* indicates the country and *t=1995,…, 2016* denotes the year.

In the system (4), the first equation accounts for the direct effects of the causes on corruption; from the second to the seven equations we model the interactions among causes of corruption. The path-coefficients estimated in these six equations allow to estimate indirect (mediated) effects of the causes on *S-CPI*. Finally, the last equation accounts the consequence of corruption on the economic system and it is included to improve the reliability of the estimates according to Duncan's (1975) remark (i.e. the meaning of the latent variable depends completely on how precisely we select causes and consequences in the SEM specification). In this sense, the inclusion within the empirical model of the effect of corruption on the socio-economic development allows to better outline our latent construct.

Due to the prediction-oriented focus of the proposed SEM, we deal with presence of missing values in the dataset by applying different missing data treatments. First, we employ the pairwise deletion method[16]. This option is applied to all the models because retains as much information as possible. The second treatment is based on the replacement of missing values by interpolation. In particular, we use three different datasets in our empirical analysis as a function of the replacement used: (1) a dataset, labelled by the acronym "MV", where pairwise deletion is applied with no replacement; (2) a dataset, labelled with "I", where we first replace missing values by a linear interpolation - i.e. calculated using the last valid value before the missing value and the first valid value after the missing - later we apply

[16] This option deletes those observations that exhibit missing values in each pair of manifest variables. Accordingly, the mean values and standard deviations computed are based on all available data for each variable while estimated correlations are based on all data available for each pair of variables.

pairwise deletion; (3) a dataset, labelled as "IFB", in which we apply, in this order, linear Interpolation (I), "Forward" Interpolation (i.e. copying previous non-missing value downwards) and "Backward" Interpolation (i.e. copying next non-missing value upwards) and, lastly, the pairwise deletion.

5. Empirical Results

We estimate three PLS-SEM[17] by using the previous missing data treatment (MV, I and IFB). The first one is the widest SEM specification described by the system of equation (4) and figure 1 (labelled as model 1). The model 2 is a restricted version of the model 1 in which the non-significant path-coefficients are omitted from the *inner model* as suggested by the standard advices for PLS-SEM specification (e.g. Garson 2016). Finally, as robustness check we consider a restricted version of model 2 (labelled as model 3) in which starting from model 2, we drop all the latent variables related to a single binary indicator (i.e. colonial heritage). This third model specification is based on the Hair et al.'s (2012) statement that PLS-SEM findings where binary single indicators are used to measure endogenous construct should be considered with caution. The statistical reason is that PLS-SEM iterative algorithm estimate the path coefficients within the *inner model* by OLS regressions therefore, since in the case of single dichotomic indicator of an endogenous latent variable the latent scores are equal to the normalized value of its binary indicator, the OLS assumption that "*the endogenous latent variable scores to be continuous, […] cannot be met in such a set-up"* (Hair et al. 2012: 421).[18]

[17] The estimates are calcualted by "SmartPLS 3.0" software developed by Ringle et al. (2015).

[18] See Bodoff and Ho (2016) for a different conclusion about the PLS-SEM's ability to handle models with observable binary variables in the case of latent variable with a single binary indicator. In our opinion, we don't consider Hair et al.'s (2012) argument as a pertinent argument against the use of single binary indicator, because the OLS assumption is that the errors and, not the dependent variable, are normally distributed, conditional upon the independent variables. Moreover, this assumption is not required for the consistency of OLS estimates but it becomes important when one needs to define some additional finite-sample properties and performs exact inference about the estimates and standard errors. Considering that PLS-SEM generates standard errors by bootstrapping procedures, thus a normal distribution of endogenous latent scores does not seem as a so relevant cause of caution for PLS-SEM.

Once the SEM models have been specified and PLS-algorithm generates the estimates, Hair et al. (2014) suggest to evaluate first the reliability and validity of the latent variables in the outer models and, only if the outer models are reliable, to evaluate the reliability of inner model. Accordingly, in Table 1 we report the outer loadings, which are the bivariate correlations between the indicator and the latent construct for reflective[19] model.

[19] Formative outer models are based on different concepts than reflective outer model and therefore require different evaluative measures. Taking into account that we specify formative models only to merge four dummies variables in two (US with Australian colonies and Belgian twith Dutch colonies), we omit to discuss these assessment indexes. However, by applying the two most common tests for formative outer model – i.e. to have loadings coefficients > 0.5 and a multicollinearity among the formative indicators measured by the variance inflation factor (VIF) below 4 – we find empirical support for the validity of the two contructs on colonial heritage.

Table 1: Standardized Outer Loadings – Model 1, 2, 3 (MV; I; IFB)

Latent Construct	Manifest Var.	Mod. 1-MV	Mod. 2-MV	Mod. 3-MV	Mod. 1-I	Mod. 2-I	Mod. 3-I	Mod. 1-IFB	Mod. 2-IFB	Mod. 3-IFB
Corruption →	bci_bci	0.86[a]	0.86[a]	0.86[a]	0.89[a]	0.89[a]	0.89[a]	0.94[a]	0.94[a]	0.94[a]
	hf_govint_R	0.85[a]	0.85[a]	0.85[a]	0.88[a]	0.88[a]	0.88[a]	0.93[a]	0.93[a]	0.93[a]
	ti_cpi_R	0.95[a]	0.95[a]	0.95[a]	0.97[a]	0.97[a]	0.97[a]	0.97[a]	0.97[a]	0.97[a]
	wbgi_cce_R	0.91[a]	0.91[a]	0.91[a]	0.91[a]	0.91[a]	0.91[a]	0.98[a]	0.98[a]	0.98[a]
	vdem_corr	0.81[a]	0.81[a]	0.81[a]	0.84[a]	0.84[a]	0.84[a]	0.93[a]	0.93[a]	0.93[a]
Education →	wdi_gersf	0.89[a]	0.89[a]	0.89[a]	0.92[a]	0.92[a]	0.92[a]	0.94[a]	0.94[a]	0.92[a]
	wdi_gert	0.87[a]	0.87[a]	0.87[a]	0.90[a]	0.90[a]	0.90[a]	0.91[a]	0.91[a]	0.91[a]
	gea_ea2534f	0.75[a]	0.75[a]	0.75[a]	0.83[a]	0.83[a]	0.83[a]	0.93[a]	0.93[a]	0.93[a]
Fractionaliz. →	al_ethnic	0.94[a]	0.94[a]	0.94[a]	0.94[a]	0.94[a]	0.94[a]	0.94[a]	0.94[a]	0.94[a]
	al_language	0.89[a]	0.89[a]	0.89[a]	0.89[a]	0.89[a]	0.89[a]	0.89[a]	0.89[a]	0.89[a]
	al_religion	0.21[a]	0.21[a]	0.21[a]	0.20[a]	0.21[a]	0.21[a]	0.20[a]	0.20[a]	0.21[a]
Media Freedom →	fhp_score_R	0.86[a]	0.86[a]	0.86[a]	0.91[a]	0.91[a]	0.91[a]	0.92[a]	0.92[a]	0.92[a]
	wdi_internet	0.63[a]	0.63[a]	0.63[a]	0.64[a]	0.64[a]	0.64[a]	0.65[a]	0.65[a]	0.65[a]
	wbgi_vae	0.96[a]	0.96[a]	0.96[a]	0.96[a]	0.96[a]	0.96[a]	0.96[a]	0.96[a]	0.96[a]
	vdem_mecorrpt	0.83[a]	0.83[a]	0.83[a]	0.87[a]	0.87[a]	0.87[a]	0.89[a]	0.89[a]	0.89[a]
Natural Resources →	ross_gas_value_pc	0.92[a]	0.92[a]	0.92[a]	-0.18	-0.18	-0.18	-0.19[c]	-0.19[c]	-0.19[c]
	ross_oil_value_pc	0.89[a]	0.89[a]	0.89[a]	0.86[a]	0.86[a]	0.86[a]	0.79[a]	0.79[a]	0.79[a]
Oil Rent →	wdi_oilrent	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)
Quality Democracy →	ht_partsz	-0.51[a]	-0.51[a]	-0.51[a]	-0.50[a]	-0.50[a]	-0.50[a]	-0.50[a]	-0.50[a]	-0.50[a]
	gsd_cg	0.91[a]	0.91[a]	0.91[a]	0.92[a]	0.92[a]	0.92[a]	0.96[a]	0.96[a]	0.96[a]
	gsd_fr	0.93[a]	0.93[a]	0.93[a]	0.95[a]	0.95[a]	0.95[a]	0.97[a]	0.97[a]	0.97[a]
	p_democ	0.82[a]	0.82[a]	0.82[a]	0.89[a]	0.89[a]	0.89[a]	0.85[a]	0.85[a]	0.85[a]
	wbgi_pve	0.61[a]	0.61[a]	0.61[a]	0.62[a]	0.62[a]	0.62[a]	0.64[a]	0.64[a]	0.64[a]
	vdem_partipdem	0.87[a]	0.87[a]	0.87[a]	0.89[a]	0.89[a]	0.89[a]	0.92[a]	0.92[a]	0.92[a]
Quality Governm. →	cspf_sfi_R	0.79[a]	0.79[a]	0.79[a]	0.84[a]	0.84[a]	0.84[a]	0.86[a]	0.86[a]	0.86[a]
	icrg_qog	0.88[a]	0.88[a]	0.88[a]	0.93[a]	0.93[a]	0.93[a]	0.99[a]	0.99[a]	0.94[a]
	wbgi_gee	0.90[a]	0.90[a]	0.90[a]	0.90[a]	0.90[a]	0.90[a]	0.91[a]	0.91[a]	0.91[a]
Quality Regulation →	fi_ftradeint_pd	0.85[a]	0.85[a]	0.85[a]	0.90[a]	0.90[a]	0.90[a]	0.89[a]	0.89[a]	0.89[a]
	fi_index_pd	0.88[a]	0.88[a]	0.88[a]	0.83[a]	0.83[a]	0.83[a]	0.88[a]	0.88[a]	0.88[a]
	hf_business	0.69[a]	0.69[a]	0.69[a]	-0.33[a]	-0.33[a]	-0.33[a]	0.80[a]	0.80[a]	0.80[a]
	wbgi_rqe	0.80[a]	0.80[a]	0.80[a]	-0.60[a]	-0.60[a]	-0.60[a]	0.89[a]	0.89[a]	0.89[a]
Quality Judic. Syst. →	fi_legprop_pd	0.90[a]	0.90[a]	0.90[a]	0.91[a]	0.91[a]	0.91[a]	0.91[a]	0.91[a]	0.91[a]
	h_j	0.65[a]	0.65[a]	0.65[a]	0.70[a]	0.70[a]	0.70[a]	0.74[a]	0.74[a]	0.74[a]
	hf_prights	0.79[a]	0.79[a]	0.79[a]	0.84[a]	0.84[a]	0.84[a]	0.87[a]	0.87[a]	0.87[a]
	vdem_jucorrdc	0.76[a]	0.76[a]	0.76[a]	0.82[a]	0.82[a]	0.82[a]	0.87[a]	0.87[a]	0.87[a]
	wbgi_rle	0.88[a]	0.88[a]	0.88[a]	0.90[a]	0.90[a]	0.90[a]	0.93[a]	0.93[a]	0.93[a]
Size of Public Sect. →	fi_sog_pd	0.80[a]	0.80[a]	0.80[a]	0.48[a]	0.48[a]	0.48[a]	0.81[a]	0.81[a]	0.81[a]
	ggfce_fce_R	0.75[a]	0.75[a]	0.75[a]	0.91[a]	0.91[a]	0.91[a]	-0.83[a]	-0.83[a]	-0.83[a]
	hf_govt	0.78[a]	0.78[a]	0.78[a]	0.87[a]	0.87[a]	0.87[a]	0.84[a]	0.84[a]	0.84[a]
Decentralization →	dpi_auton	1.00	--	--	1.00	--	--	1.01	--	--
	pt_federal	0.11	--	--	0.11	--	--	-0.08	--	--
Never Colony →	ht_c_NO_col	1(fixed)	--	--	1(fixed)	--	--	1(fixed)	--	--
French Colony →	ht_c_French	1(fixed)	1(fixed)	--	1(fixed)	1(fixed)	--	1(fixed)	1(fixed)	--
Spanish Colony →	ht_c_Spanish	1(fixed)	1(fixed)	--	1(fixed)	1(fixed)	--	1(fixed)	(fixed)	--
US & Austral. Col. ←	ht_c_Australian	0.71[a]	0.71[a]	--	0.72[a]	0.72[a]	--	0.76[a]	0.76[a]	--
	ht_c_US	0.70[a]	0.70[a]	--	0.69[a]	0.69[a]	--	0.65[a]	0.65[a]	--
Portug. Colony →	ht_c_Portuguese	1(fixed)	1(fixed)	--	1(fixed)	1(fixed)	--	1(fixed)	1(fixed)	--
Belgian & Dutch Col. ←	ht_c_Belgian	0.85[a]	0.84[a]	--	0.86[a]	0.86[a]	--	0.90[a]	0.90[a]	--
	ht_c_Dutch	0.52[a]	0.52[a]	--	0.49[a]	0.49[a]	--	0.43[a]	0.43[a]	--
British Colony →	ht_c_British	1(fixed)	--	--	1(fixed)	--	--	1(fixed)	1(fixed)	--
% Catholics →	lp_catho80	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	--
% Muslims →	lp_muslim80	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	--
% Protestants →	lp_protmg80	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	1(fixed)	--
Economic Development →	wdi_acel	0.84[a]	0.84[a]	0.84[a]	0.93[a]	0.93[a]	0.93[a]	0.95[a]	0.95[a]	0.95[a]
	wdi_gdpcapcon2010	0.69[a]	0.69[a]	0.69[a]	0.68[a]	0.68[a]	0.68[a]	0.72[a]	0.72[a]	0.72[a]
	wdi_lifexp	0.86[a]	0.86[a]	0.86[a]	0.86[a]	0.86[a]	0.86[a]	0.89[a]	0.89[a]	0.89[a]
	pwt_hci	0.90[a]	0.90[a]	0.90[a]	0.84[a]	0.84[a]	0.84[a]	0.85[a]	0.85[a]	0.85[a]
	undp_hdi	0.93[a]	0.93[a]	0.93[a]	0.90[a]	0.90[a]	0.90[a]	0.91[a]	0.91[a]	0.91[a]

Note: [a, b, c]denote significant at 1%, 5% and 10% level; "→" denotes reflective outer model; "←"denotes formative model.

A first step to assess reflective outer models is to check the internal consistency reliability of each latent construct by using the index of *composite reliability* (CR). A common rule of thumb (e.g. Garson 2016) suggests that values of 0.70 or higher is good for confirmatory purposes of SEM model. Every outer model shows a CR higher than 0.8 with exclusion of "*Decentralization*" which ranges between 0.46 (for IFB) and 0.58 (for "MV").

A second step consists in assessing convergent and discriminant validity of outer model. Following Hair et al. (2014) convergent validity occurs when each outer loading is above 0.70 (see Table 1) and when each construct's average variance extracted (AVE) is 0.50 or higher. All these checks of outer models confirm the reliability of the outer models, with exclusion of the outer loadings in the measurement model of "*Decentralization*". Accordingly we drop this latent variable in the model 2 and 3.[20] For discriminant validity assessment – which represents the extent to which the construct is empirically distinct from other constructs - Henseler et al. (2015) demonstrate that the lack of discriminant validity is better detected by the heterotrait-monotrait (HTMT) ratio. They suggest that a HTMT value below 0.90 provides evidence for discriminant validity between a given pair of reflective constructs. To save space, we omit to report these 9 matrixes (i.e. 3 specifications for 3 missing values treatments) with a 23 x 23 (η x η) dimension. In brief, this analysis reveals the hypothesis of discriminant validity holds for all the 9 estimated models because the HTMT values above the thereshold range between 3% and 6% of the total numbers of estimated HTMT ratios for each model.

[20] For completeness , we also find that some of the outer models specified for "*Colonial heritage*", "Religion belonging" and "oil rent" shown CR and AVE greater than 1 or missed. However, it is due to the specification for their measurement model with a single and/or binary variables.

Table 2: Standardized Path Coefficients (Direct Effects) Inner Model 1 and 2 and 3 (MV; I; IFB)

Cause → Corruption (Direct Effect)		Model 1- MV	Model 2- MV	Model 3- MV	Model 1- I	Model 2- I	Model 3- I	Model 1-IFB	Model 2-IFB	Model 3-IFB
Quality of Jud. System → Corruption	β_{61}	-0.68[a]	-0.70[a]	-0.65[a]	-0.71[a]	-0.72[a]	-0.66[a]	-0.69[a]	-0.70[a]	-0.64[a]
Quality of Government → Corruption	β_{41}	-0.32[a]	-0.30[a]	-0.30[a]	-0.24[a]	-0.23[a]	-0.24[a]	-0.32[a]	-0.32[a]	-0.32[a]
% Protestant → Corruption	$\beta_{21,1}$	-0.10[a]	-0.10[a]	-0.10[a]	-0.09[a]	-0.09[a]	-0.10[a]	-0.09[a]	-0.09[a]	-0.10[a]
Spanish Colony → Corruption	$\beta_{14,1}$	-0.08[a]	-0.09[a]	--	-0.09[a]	-0.10[a]	--	-0.12[a]	-0.13[a]	--
Quality of Democracy → Corruption	β_{31}	0.06[a]	0.08[a]	0.05[a]	0.13[a]	0.14[a]	0.09[a]	0.15[a]	0.15[a]	0.11[a]
Belgian and Dutch Colony → Corruption	$\beta_{17,1}$	-0.05[a]	-0.06[a]	--	-0.07[a]	-0.07[a]	--	-0.09[a]	-0.09[a]	--
Size of Public Sector → Corruption	β_{71}	0.05[a]	0.05[a]	0.03[a]	-0.09[a]	-0.09[a]	-0.09[a]	0.06[a]	0.06[a]	0.03[a]
Quality of Regulation → Corruption	β_{51}	-0.05[a]	-0.04[a]	-0.03[a]	-0.06[a]	-0.05[a]	-0.02[b]	-0.09[a]	-0.09[a]	-0.06[a]
French Colony → Corruption	$\beta_{13,1}$	-0.05[b]	-0.05[a]	--	-0.07[a]	-0.07[a]	--	-0.09[a]	-0.09[a]	--
Fractionaliz. → Corruption	β_{81}	-0.04[a]	-0.05[a]	-0.05	-0.05[a]	-0.06[a]	-0.05[a]	-0.06[a]	-0.06[a]	-0.06[a]
Oil Rent → Corruption	$\beta_{10,1}$	0.04[a]	0.04[a]	0.04[a]	-0.02[a]	-0.03[a]	-0.02[a]	-0.02[a]	-0.02[a]	-0.03[a]
% Muslim → Corruption	$\beta_{20,1}$	-0.04[a]	-0.04[a]	--	-0.03[a]	-0.03[a]	--	-0.03[a]	-0.03[a]	--
Natural Resources → Corruption	β_{91}	-0.04[a]	-0.04[a]	-0.04[a]	0.03[a]	0.03[a]	0.03[a]	0.01[b]	0.01[b]	0.02[a]
Portuguese Colony → Corruption	$\beta_{16,1}$	-0.03[b]	-0.04[a]	--	-0.04[a]	-0.04[a]	--	-0.05[a]	-0.06[a]	--
% Catholic → Corruption	$\beta_{19,1}$	0.03[a]	0.03[a]	-0.03[a]	0.04[a]	0.04[a]	0.03[a]	0.05[a]	0.05[a]	0.03[a]
US and Australian colony → Corruption	$\beta_{15,1}$	0.02[b]	0.02[a]	--	0.01	0.02[a]	--	0.01[*]	0.01[a]	--
No Colony → Corruption	$\beta_{12,1}$	0.02	--	--	0.02	--	--	0.00	--	--
Media Freedom → Corruption	β_{21}	-0.01	-0.03[c]	-0.01	-0.04[a]	-0.05[a]	-0.02[c]	-0.08[a]	-0.08[a]	-0.06[a]
Decentralization → Corruption	$\beta_{11,1}$	0.01	--	--	0.02	--	--	0.01	--	--
British Colony → Corruption	$\beta_{18,1}$	-0.01	--	--	-0.02	--	--	-0.05[a]	-0.05[a]	--
Cause → Cause→ Corrup.(Indirect Effect)										
Q. of Regulation → Q. of Judicial System	$\beta_{5,6}$	0.90[a]	0.90[a]	0.90[a]	0.82[a]	0.82[a]	0.82[a]	0.86[a]	0.86[a]	0.86[a]
Media Freedom → Q. of Democracy	$\beta_{22,2}$	0.84[a]	0.84[a]	0.84[a]	0.84[a]	0.84[a]	0.84[a]	0.89[a]	0.89[a]	0.89[a]
Q. of Government → Q. of Regulation	β_{45}	0.78[a]	0.78[a]	0.78[a]	0.73[a]	0.73[a]	0.73[a]	0.90[a]	0.90[a]	0.90[a]
Education → Economic Development	$\beta_{22,23}$	0.76[a]	0.76[a]	0.76[a]	0.76[a]	0.76[a]	0.76[a]	0.75[a]	0.75[a]	0.75[a]
Education → Media Freedom	$\beta_{22,2}$	0.70[a]	0.70[a]	0.70[a]	0.68[a]	0.68[a]	0.68[a]	0.64[a]	0.64[a]	0.64[a]
Q. of Democracy → Q. of Government	β_{34}	0.64[a]	0.65[a]	0.65[a]	0.68[a]	0.68[a]	0.68[a]	0.68[a]	0.68[a]	0.68[a]
Fractionalization → Q. of Government	β_{94}	-0.23[a]	-0.23[a]	-0.23[a]	-0.23[a]	-0.24[a]	-0.24[a]	-0.23[a]	-0.24[a]	-0.24[a]
Fractionalization → Decentralization	$\beta_{9,12}$	-0.15	--	--	-0.14	--	--	-0.15	--	--
Natural Resources → Economic Developm.	$\beta_{23,10}$	0.11[a]	0.11[a]	0.11[a]	0.01	0.01	0.01	0.02	0.02	0.02
Education → Q. of Democracy	$\beta_{22,3}$	0.09[a]	0.09[a]	0.09[a]	0.08[a]	0.08[a]	0.08[a]	0.03[a]	0.03[a]	0.03[a]
Decentralization → Q. of Government	$\beta_{12,4}$	0.01	--	--	0.01	--	--	0.01	--	--
Corrupt.→ Consequences (Direct Effect)										
Corruption → Economic Development	$\beta_{1,23}$	-0.30[a]	-0.30[a]	-0.30[a]	-0.26[a]	-0.26[a]	-0.26[a]	-0.22[a]	-0.22[a]	-0.22[a]

Note: [a],[b],[c] denote significant at 1%, 5% and 10% level.

Table 2 shows that the estimated path-coefficients are qualitatively robust between the three model specifications (model 1, 2 and 3). These estimates are also robust to the three different treatments of missing values (i.e. MV, I and IFB) with the exclusion of the effect of "*British Colony"* on "*Corruption"* ($\beta_{18,1}$) and of the influence of size of "*Natural Resources"* on socio-economic development ($\beta_{23,10}$),

All the path-coefficients have the expected signs, with the exclusion of the model 1 with no replacement of missing values in which "*Media Freedom*" and "*British colony*" have not statistically significant effect on corruption (1-MV) in comparison to the estimates based on the replacement of missing values (1-I and 1-IFB). In these cases the direct effects estimated using missing values replacement empirically support the prevalent literature on a negative correlation between Media freedom and British heritage on perceived corruption.

The standard criteria to assess the inner model are based on the evaluation of coefficient of determination (R^2), the Stone-Geisser Q^2 and the statistical significance of standardized path-coefficients. In particular, the rules of thumb are that: (1) the coefficient of determination (R^2) - which represents the amount of explained variance of each endogenous construct should show R^2 value higher than 0.66 to infer a substantial effect of exogenous on endogenous variable, while lower than 0.2 indicates weak effect (Henseler et al. 2009); (2) the cross-validated redundancy, also known as Stone-Geisser Q^2 - which assesses the inner model's predictive relevance, should be higher than 0.35 in order to reveal a large predictive relevance of a certain latent variable while, in case of a negative Q^2 the scholar should come to the conclusion of absence of predictive relevance (Cohen 1988); (3) the statistical significance of standardized path-coefficients where, due to the standardization, a path-coefficient larger than 0.70 indicates a relevant direct marginal effect.

Lastly, as PLS-SEM doesn't have a standard goodness-of-fit statistic,[21] Tenenhaus et al. (2004) propose an assessment of the overall SEM model combining average variance extracted (AVE) by each outer model and variance explained (R^2) by each inner model. Although the label of this measure ("*Goodness of Fit*" - *GoF*) may be misleading because there is no global fitting function to be evaluated to determine the goodness of the model,[22] we report the *GoF* only for completeness of output reporting but without consider it as an "overall" goodness of fit measure. *GoF* is calculated as $\sqrt{\overline{AVE} * \overline{R^2}}$ and is bounded between 0 and 1, where higher values indicate better model performance. Table 3 reports these statistics.

[21] See Henseler and Sarstedt (2013) for a simulation analysis that shows as the goodness-of-fit statistic in PLS-SEM is not suitable for model validation.

[22] An additional reason of caution is pointed out by Hair et al. (2012). They state that since the GoF is based on reflective outer models' communalities, this index is conceptually inappropriate whenever the SEM includes also formative outer models or single indicator constructs. This occurs for the models 1 and 2 in our SEM specifications.

Table 3: Inner Model assessment (R^2; Q^2) and Goodness of Fit index (*GoF)*

Endogenous Latent	1 - MV		2 - MV		3 - MV		1 - I		2 - I		3 - I		1 - IFB		2 - IFB		3 - IFB	
Inner Assessment	R^2	Q^2	R^2	Q^2	R^2	Q^2	R^2	Q^2	R^2	Q^2	R^2	Q^2	R^2	Q^2	R^2	Q^2	R^2	Q^2
Corruption	0.91	0.71	0.91	0.71	0.90	0.70	0.92	0.75	0.93	0.79	0.91	0.74	0.92	0.74	0.93	0.79	0.90	0.78
Decentralization	0.02	0.02	--	--	--	--	0.02	0.02	--	--	--	--	0.02	0.02	--	--	--	--
Media Freedom	0.36	0.24	0.36	0.24	0.36	0.24	0.37	0.25	0.41	0.28	0.37	0.25	0.37	0.25	0.41	0.28	0.36	0.28
Quality of Democracy	0.85	0.55	0.85	0.55	0.85	0.55	0.86	0.56	0.88	0.57	0.86	0.56	0.86	0.56	0.88	0.57	0.85	0.57
Quality of Government	0.63	0.49	0.63	0.49	0.63	0.49	0.65	0.52	0.66	0.53	0.65	0.52	0.65	0.52	0.66	0.53	0.63	0.53
Quality of Regulation	0.70	0.48	0.70	0.48	0.70	0.48	0.59	0.30	0.76	0.56	0.59	0.30	0.59	0.30	0.76	0.56	0.70	0.56
Quality of Judicial Syst.	0.72	0.47	0.72	0.47	0.72	0.47	0.61	0.42	0.75	0.54	0.61	0.42	0.61	0.42	0.75	0.54	0.72	0.54
Economic Develop.	0.80	0.57	0.80	0.57	0.80	0.57	0.83	0.59	0.86	0.63	0.83	0.59	0.83	0.59	0.86	0.63	0.80	0.63
Goodness of Fit	**0.76**		**0.81**		**0.80**		**0.73**		**0.81**		**0.75**		**0.78**		**0.75**		**0.76**	

Note: Q^2 is the "Construct cross-validated redundancy" score calculated by Smart PLS 3.

As the three criteria for inner model assessment are concerned, Table 3 shows as: (1) the R^2 are higher than 0.67 with exclusion of constructs "*Decentralization*", "*Media Freedom*" and "*Quality of Government*". However the latter has a score of the coefficient of determination very close to the minimum threshold (about 0.65). It is relevant to point out as the explained variance of the key variable of this analysis (i.e. "*Corruption*" has the highest value of R^2 (about 0.93). (2) Looking at the Stone-Geisser Q^2, the highest degree of predictive relevance is for the latent variable "*Corruption*". As the other endogenous constructs concerns, they have "high" predictive relevance (Q^2>0.35) with two exceptions: *Media Freedom* – that a Q^2 in the range 0.25 - 0.35 shows "medium" effect size and "*Decentralization*" that according to the usual thresholds of Q^2 index has a predictive relevance lower than "small" (i.e. $Q^2 < 0.02$). (3) The standardized path coefficients are all statistically significant and qualitatively robust to alternative model specifications and treatments of missing values (see Table 2).

With reference to the *GoF* scores, all the models have a convincing (larger than 0.70) overall variance explained.

In conclusion, due to the robustness of results across the three specifications, we opt for the model 2, since it is considered as the best model. Although model 2 and 3 have the same (good) properties in terms of statistical reliability, model 2 has a more complete specification due to its inclusiveness of more relationships between corruption and its causes. Taking into account that PLS-SEM model is a predicted-oriented approach, once that the model 2 has been selected, the choice between the favorite treatment of missing values (MV, I or IFB) is based on the analysis of the characteristics of the

estimated *S-CPI* scores. Following the current literature, we standardize the estimated latent scores of "perceived corruption" ($\hat{x}_{it}$) in order to get an index ranging between 0-100. The Standardization is based on the following formula:

$$S-CPI_{i,t} = 100 \frac{\hat{x}_{i,t} - \underset{\forall i,\forall t}{Min}\left(\hat{x}_{i,t}\right)}{\underset{\forall i,\forall t}{Max}\left(\hat{x}_{i,t}\right) - \underset{\forall i,\forall t}{Min}\left(\hat{x}_{i,t}\right)} \tag{5}$$

where, for the Model 2 –IFB, the values of $\underset{\forall i,\forall t}{Min}\left(\hat{x}_{i,t}\right)$ = -2.562 and $\underset{\forall i,\forall t}{Max}\left(\hat{x}_{i,t}\right) = 1.561$.

Although the different treatments of missing values don't strongly change the ranking of countries (see Table 4) and the correlations between the S-CPI indexes estimated by the original dataset (MV) and the dataset with replacement are very high: 99.6% (MV vs I) and 98.5% (MV vs IFB), from a graphical analysis some relevant issues emerge against the use of MV dataset.

Figure 2: Annual World Average of the Index of standardized S-CPI - Model 2

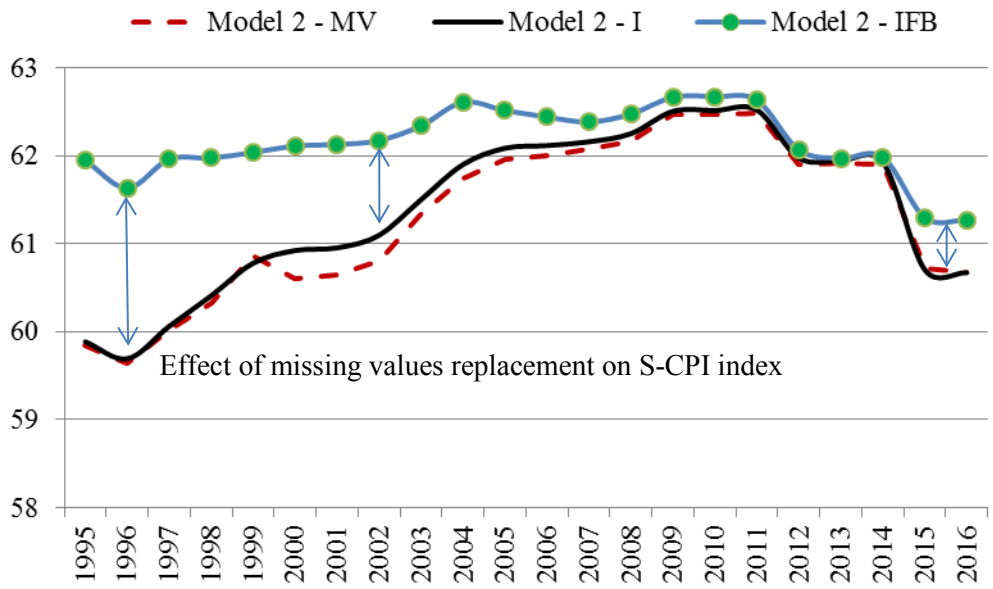


Figure 2 shows that, while the estimated coefficients and assessment indexes are robust to different missing treatments (Tables 1-3), the world average of *S-CPI* scores are biased due to the presence of missing values during the first decade of time range (1995-2005) and during the last two years of the sample (2015-2016). This result indirectly confirms Hair et al.'s (2016) result which identifies a

maximum threshold of missing value at 15% as rule of thumb to consider the presence of missing values as a problem for the estimates.

In our original sample (MV), in fact, missing values are about 13.5% of potential sample (28,322 on 210,540 potential observations). On the contrary, if the IFB replacement of missing values is applied, the percentage of missing values decreases to 4.6% of potential sample (9,760 missed observations).

Accordingly, we conclude that, for descriptive analysis of perceived corruption in developed countries focused on the last decade, the best estimates of the S-CPI may be calculated by applying the pairwise deletion and with no replacement of missing values (MV) with model 2 specification, because these estimates are more conservative. On the contrary, if a scholar focuses also on developing countries (i.e. countries that usually have variables with more missing values than developed ones) and/or they are looking for a longer time span thus, the model 2 with IFB replacement strategy combined with pairwise deletion, it is considered more reliable and with a greater cross-countries and temporal comparability.

This conclusion is also supported by an additional analysis on how the two replacement treatments affect the presence of outliers in the predicted values. This analysis deals with the empirical evidence that PLS-SEM estimates may be distorted by the presence of outliers. Consequently, we define as "outlier" a predicted value of *S-CPI* if, in a country, the difference between the standardized (unstandardized) latent score at the time *t* is higher or lower than 100% (200%) of the *S-CPI* value estimated at the time *t-1*. Table 4 shows how many outliers are generated by the PLS-SEM by employing the three replacement strategies with the model 2 specification. Conclusively, the estimates based on IFB treatments minimize the outliers in both the predicted raw and standardized score of *S-CPI*. Moreover, looking at the standardized index with IFB replacement, we note as this version of the index does not have "outliers". In view of that, it is considered as the most realistic picture of the dynamics of perceived corruption.

Table 4. Presence of outliers in the estimated (Raw and standardized) S-CPI based on Model 2.

Raw index	MV	I	IFB	**Standardized index**	MV	I	IFB
Increases more than 200%	69	53	26	Increases more than 100%	38	7	0
Decreases more than 200%	34	27	29	Decreases more than 100%	0	0	0
Total	**103**	**80**	**55**	Total	**38**	**7**	**0**

According to assessment statistics for the inner, outer and overall model, the graphical analysis of missing values, and investigation on outliers, we conclude that the restricted SEM model with IFB adjustments of missing values (model 2 – IFB) has the best performances.

5.1 Country Average Estimates of S-CPI index aggregated by Geographical area

Table 5.a-c reports the country averages of the estimated S-CPI index grouping by geographical area. We highlight in bold (grey color the background of the cell) values for the countries ranked in the first (last) quartile of the distribution according to the level of perceived corruption. To show the robustness of S-CPI index we present the estimates based on the three replacement strategies and model 2.

Table 5.a: Average Model 2, 1995-2016

	Country	MV	I	IFB
South-East Asia	Singapore	**8.99**	**7.37**	**5.77**
	Malaysia (1966-)	52.59	52.25	51.78
	Thailand	68.06	68.13	68.41
	Vietnam	72.21	72.52	73.21
	Philippines	75.74	75.95	76.26
	Indonesia	78.65	79.32	79.66
	Laos	77.84	78.38	80.02
	Cambodia	79.95	80.63	83.69
	Myanmar	85.67	86.59	90.11
	Average	***66.63***	***66.79***	***67.65***
East Asia	Japan	**27.02**	**26.13**	**25.05**
	Taiwan	**42.86**	**42.33**	**41.77**
	Korea, South	**47.06**	**46.73**	**46.63**
	China	66.09	66.23	66.28
	Mongolia	68.90	69.15	69.37
	Korea, North	85.03	85.87	92.64
	Average	***56.16***	***56.07***	***56.94***
South Asia	Sri Lanka	64.70	64.76	65.36
	India	68.55	68.73	69.05
	Maldives	70.01	70.79	73.23
	Nepal	78.96	79.35	81.76
	Pakistan (1971-)	80.48	81.33	81.97
	Bangladesh	84.89	86.81	87.77
	Afghanistan	80.74	81.84	89.20
	Average	***75.48***	***76.23***	***78.33***

	Country	MV	I	IFB
The Caribbean	Barbados	**32.24**	**30.84**	**26.80**
	Trinidad and Tobago	57.61	57.25	56.57
	Jamaica	59.62	59.65	59.99
	Suriname	64.05	63.88	64.38
	Belize	66.02	66.08	67.50
	Guyana	72.25	72.44	74.75
	Average	***58.63***	***58.36***	***58.33***
The Pacific	Fiji	57.72	57.41	57.78
	Solomon Islands	63.58	64.06	67.67
	Papua New Guinea	75.59	76.41	78.85
	Average	***65.63***	***65.96***	***68.10***

Table 5.b: Country Average 1995-2016 - Model 2.

	Country	MV	I	IFB
Eastern Europe and post-Soviet Union	Estonia	**35.87**	**35.32**	**33.99**
	Slovenia	**42.15**	**41.37**	**40.10**
	Poland	**48.46**	**47.90**	**47.46**
	Hungary	**49.23**	**48.64**	**48.59**
	Lithuania	50.90	50.61	50.76
	Czech Republic	52.37	52.00	51.90
	Latvia	53.90	53.85	54.27
	Slovakia	57.29	57.12	57.49
	Croatia	59.89	60.02	61.09
	Bulgaria	63.72	63.79	64.52
	Georgia	62.98	64.15	65.27
	Macedonia	66.42	67.29	68.20
	Romania	68.23	68.52	68.98
	Belarus	68.78	69.03	69.38
	Bosnia and Herzegovina	69.98	70.23	72.19
	Moldova	74.01	74.37	75.59
	Armenia	74.61	75.41	76.43
	Albania	75.30	76.31	77.66
	Kazakhstan	78.11	78.82	81.00
	Russia	80.62	81.24	81.99
	Ukraine	80.44	81.19	82.48
	Azerbaijan	82.51	83.37	85.36
	Tajikistan	81.53	82.37	85.91
	Kyrgyzstan	82.70	83.98	86.07
	Uzbekistan	84.08	84.79	87.64
	Turkmenistan	86.81	87.55	91.68
	Average	***66.57***	***66.89***	***67.92***

	Country	MV	I	IFB
Latin America	Chile	**28.41**	**27.28**	**26.32**
	Uruguay	**34.12**	**33.31**	**32.55**
	Costa Rica	**46.29**	**45.65**	**44.92**
	Cuba	59.18	58.89	58.27
	Brazil	63.41	63.30	63.57
	Panama	63.61	63.71	64.32
	Peru	65.52	65.71	65.93
	El Salvador	66.91	67.32	67.92
	Colombia	67.87	68.10	68.56
	Argentina	68.62	68.68	69.23
	Mexico	68.98	69.15	69.54
	Guatemala	74.57	75.19	76.03
	Ecuador	74.82	75.51	76.10
	Bolivia	75.96	76.28	76.88
	Nicaragua	76.62	77.29	78.14
	Dominican Republic	76.85	77.21	78.46
	Honduras	78.61	79.46	80.86
	Venezuela	84.92	85.44	86.26
	Paraguay	83.31	84.71	86.45
	Haiti	85.05	85.91	88.25
	Average	***67.18***	***67.40***	***67.93***

	Country	MV	I	IFB
North Africa & the Middle East	Israel	**35.83**	**34.93**	**33.84**
	Qatar	**40.03**	**39.68**	**35.53**
	United Arab Emirates	**39.10**	**38.88**	**36.62**
	Cyprus (1975-)	**40.04**	**39.18**	**36.82**
	Oman	**41.99**	**41.43**	**38.97**
	Bahrain	**49.11**	**48.77**	**46.51**
	Saudi Arabia	53.10	53.16	52.15
	Kuwait	54.45	53.95	52.56
	Jordan	53.40	53.25	52.96
	Tunisia	57.56	57.63	57.40
	Turkey	61.52	61.65	61.65
	Morocco	65.18	65.16	65.32
	Algeria	69.76	70.30	72.30
	Egypt	73.12	73.54	73.95
	Iran	72.30	72.55	74.25
	Lebanon	78.31	78.62	80.74
	Syria	81.33	81.88	83.41
	Libya	81.23	81.81	84.61
	Yemen	85.89	86.51	88.75
	Iraq	83.73	87.30	90.20
	Average	***60.85***	***61.01***	***60.93***

Table 5.c: Average Model 2, 1995-2016

	Country	MV	I	IFB		Country	MV	I	IFB		Country	MV	I	IFB
Sub-Saharan Africa	Botswana	**39.21**	**38.58**	**37.44**	Sub-Saharan Africa	Liberia	72.58	73.88	79.14	Western Europe and North America	Denmark	**6.52**	**4.81**	**2.73**
	Cape Verde	**47.64**	**47.14**	**45.37**		Niger	76.16	76.77	79.55		New Zealand	**7.54**	**5.89**	**3.71**
	Namibia	50.66	50.20	**49.47**		Cote d'Ivoire	79.20	79.52	80.17		Finland	**8.25**	**5.95**	**3.81**
	South Africa	52.32	51.82	51.71		Comoros	74.63	75.39	80.25		Sweden	**8.96**	**7.30**	**5.84**
	Mauritius	55.75	55.47	54.47		Mali	78.08	78.59	80.30		Iceland	**14.18**	**12.66**	**8.76**
	Rwanda	58.40	58.84	59.98		Zimbabwe	80.29	80.73	81.11		Norway	**12.47**	**10.85**	**8.85**
	Lesotho	62.30	62.26	63.40		Uganda	79.77	80.48	81.29		Switzerland	**12.54**	**10.99**	**9.04**
	Ghana	64.90	64.99	65.51		Sierra Leone	79.01	80.13	82.52		Netherlands	**13.23**	**11.64**	**9.71**
	Senegal	65.96	65.95	66.40		Togo	78.03	78.55	82.59		Canada	**15.10**	**13.54**	**12.25**
	Swaziland	66.32	66.33	68.21		Kenya	81.23	82.14	82.94		Australia	**15.25**	**13.85**	**12.63**
	Zambia	67.32	67.80	68.42		Central Afr. Rep.	80.04	80.77	84.62		United Kingdom	**17.89**	**16.34**	**15.07**
	Burkina Faso	67.53	67.98	69.36		Burundi	79.57	81.05	84.69		Germany	**18.57**	**17.12**	**15.96**
	Eritrea	67.06	66.65	70.00		Guinea	81.95	82.54	86.20		Austria	**21.77**	**20.40**	**19.45**
	Malawi	69.56	69.77	70.13		Nigeria	85.13	85.92	87.14		Luxembourg	**24.26**	**22.77**	**19.78**
	Benin	70.53	70.86	72.49		Congo	83.71	84.43	87.23		Ireland	**23.78**	**22.63**	**21.42**
	Ethiopia (1993-)	71.23	71.70	72.70		Cameroon	86.25	87.29	88.19		United States	**25.73**	**24.47**	**23.66**
	Gambia	70.37	70.63	72.81		Angola	84.25	86.68	88.96		Belgium	**27.78**	**26.70**	**24.97**
	Tanzania	71.44	71.94	73.26		Guinea-Bissau	85.24	85.99	90.81		France (1963-)	**28.12**	**27.11**	**26.31**
	Djibouti	70.98	71.52	73.81		Equatorial Guinea	85.08	86.02	91.78		Spain	**34.59**	**33.57**	**33.24**
	Mozambique	73.47	74.13	74.93		Congo, Dem. Rep.	86.09	89.16	92.34		Portugal	**34.99**	**34.02**	**33.42**
	Gabon	73.25	73.78	75.03		Chad	88.50	89.29	93.60		Malta	50.28	**49.73**	**46.82**
	Mauritania	75.25	75.48	77.71		Somalia	85.28	86.49	95.21		Italy	52.84	52.36	52.49
	Madagascar	76.31	76.61	79.08		***Average***	***72.84***	***73.38***	***75.39***		Greece	56.24	55.73	55.89
											Average	***23.08***	***21.76***	***20.25***

Focusing on the "extreme cases" shown in Table 5, we find that the five nations with the lowest-rated index of perceived corruption are: Denmark, New Zealand, Finland, Sweden, and Singapore. On the other side of the ranking, the most corrupted countries are: Chad, Congo, Democratic Republic, Turkmenistan, and Iraq. The five nations showing the biggest declines in corruption (in percentage points) from 2000 to 2016 are Denmark, Finland, Iceland, Singapore, and New Zealand. The five countries with the largest increases in corruption over the period 2000-16 are: Rwanda, Georgia, Poland, Cote d'Ivoire, and Uruguay. In terms of time trend of *S-CPI*, we find a heterogeneous behavior among the geographical areas. For the sake of brevity, we cannot focus on this topic here, but looking at the worldwide trend (Figure 2), it is quite clear to identify as the perceived corruption is approximately constant up to the Great Recession, only since 2010, we observe a slight reduction in the world average of *S-CPI*.

Although an analysis of policy implications of these findings is out of the interests of this research, in the following Table, we show how from SEM findings could derive interesting normative inferences. Table 6 shows direct and indirect (i.e. mediated by other endogenous latent variables) effects for each cause of the model 2 - IFB.

Table 6: Direct, Indirect and Total Effects - Inner Model 2 (IFB)

Cause → Effect	Direct (β)	Indirect	Total
Quality of Government → Corruption	-0.317	-0.621	**-0.938**
Quality of Judicial Syst. → Corruption	-0.695	--	**-0.695**
Quality of Regulation → Corruption	-0.090	-0.600	**-0.690**
Media Freedom → Corruption	-0.080	-0.431	**-0.511**
Quality of Democracy → Corruption	0.148	-0.634	**-0.486**
Education → Corruption	--	-0.343	**-0.343**
Fractionalization → Corruption	-0.057	0.221	**0.164**
Spanish Colony → Corruption	-0.125	--	**-0.125**
Belgian Colony → Corruption	-0.091	--	**-0.091**
% Protestant → Corruption	-0.090	--	**-0.090**
French Colony → Corruption	-0.090	--	**-0.090**
Size of Public Sector → Corruption	0.058	--	**0.058**
Portuguese Colony → Corruption	-0.056	--	**-0.056**
British Colony → Corruption	-0.051	--	**-0.051**
% Catholic → Corruption	0.047	--	**0.047**
% Muslim → Corruption	-0.031	--	**-0.031**
Oil Rent → Corruption	-0.019	--	**-0.019**
Natural Resources → Corruption	0.013	--	**0.013**
US and Australian colony → Corruption	0.012	--	**0.012**

The main normative result of this analysis consists to point out how ranking based on the marginal effects of causes of corruption changes when the indirect effects are accounted for. For instance, while the quality of Judicial system has the largest direct effect on perceived corruption (β_{61}= -0.70), once we include the indirect effects, we observe that the most important determinant of corruption is a (low) "*Quality of Government"* (Total effect = -0.94). In the same way, other determinants of corruption as "*Quality of Regulation*" and "*Media Freedom*", as a consequence of their indirect effects (-0.60 and -0.43, respectively), increase of 6-7 times their effect on corruption: from β_{51}= -0.09 to a total effect of -0.69 for "*Q_reg*" and from β_{21}= -0.08 to -0.51 for "*Media_Fr*". Again, the latent construct "*Quality of democracy*", that has an unexpected positive direct marginal effect on the perceived corruption (β_{31}= 0.148), later than indirect effects are accounted for (-0.634), it turns into the expected negative coefficient in terms of total effect (-0.486). Lastly, variables as "*Education*", that has not direct effect on corruption became, in terms of total effect, the 6th more relevant factor that shapes corruption due to its effects on the other direct causes of perceived corruption.

6. Conclusions

This research examines the causes and consequences of corruption by a PLS-SEM. Approaching this phenomenon as a latent construct, we estimate an index of perceived corruption in 165 countries from 1995 to 2016.

From a methodological viewpoint, the analysis of empirical relationships between constructs that are not-directly observed (e.g. corruption) and/or intrinsically multidimensional (e.g. institutional quality, economic development) makes the PLS-SEM a worthwhile approach for this strand of literature. This methodology allows to estimate the corruption by a unified framework based on the existing theory and empirics of corruption. It is made possible by the chance that SEM gives the researcher to simultaneously specify, on the one hand, which are both the determinants that directly and/or indirectly affects corruption as well as the effects of corruption on a country's economic performances – this is the structural or inner model of the SEM-. On the other hand, SEM allows to exploit the current indexes of

perceived corruption as complementary observable measurements of this phenomenon – this is the "measurement or outer model" -.

On the positive side, the estimated *S-CPI* has two main advantages compared to the existing indexes of perceived corruption. First, it provides estimates of perceived corruption by exploiting not only the existing indexes but also the economic literate on the causes and consequences of corruption in a unified framework – consequently, our index can be considered as a "structural index" –. Second, it reduces measurement errors in two ways: (a) by using several indicators for each "unobservable" variable (e.g. corruption; quality of Institutions; socio-economic development) – accordingly, the proposed index can be considered as a "meta-index" –; (b) by following the conventional statistical remedy to enlarge the sample size in order to reduce measurement errors. Specifically, we consider about 180,000 observations (coming from 58 manifest variables concerning 165 countries over a period of 21 years). These two correlated strategies make our findings robust to different model specification and of strategies to replace missing values.

On the negative side, however, the proposed statistical approach shares the two most relevant problems of this empirical literature. First, the problem of the divergence between "perceived" and "actual" corruption" is unsolved here. Second, the PLS-SEM provides unsatisfactory solutions for the problem of endogeneity. Specifically, we know that some variables, identified in the model as "causes" of corruption, are also influenced by the perceived size of corruption (e.g. the quality of institutions). Analogously, lower socio-economic development is a "consequence" of corruption but it also indirectly affects it. Therefore, we suggest some cautions to assess the relationships between explanatory factors (or consequences) and corruption derive from one-way causal links instead of bi-directional interactions that generate feedback loops.

Lastly, we derive some normative policy implications from PLS-SEM findings by using the estimated direct and indirect (i.e. mediated by other potential causes) effects. These estimates quantify how each latent construct shapes other latent variables (e.g. perceived corruption). In general terms, we find that only focus on direct effects may be misleading. Indeed, we observe that these direct effects may be offset (i.e. *Quality of Democracy*) or strongly strengthened (e.g. *Quality of Regulation*, *Media Freedom*)

by indirect effects. More specifically, we find that the most relevant determinants of corruption at worldwide level are (in decreasing order according to the total effects): "*Quality of Government*", "*Quality of Judicial System*", "*Quality of Regulation*", "*Media Freedom*", "*Quality of Democracy*", "*Education*" and the "*Fractionalization*" of the society. For other determinants, that are often considered as important causes of corruption in the existing empirical literature, (e.g. "*Colonial Heritage*", "*Religion belonging*", "*Size of public sector*", (abundance of) "*natural resources*" and "*Oil rent*) our data confirms their statistically significance but with a minor role in explaining the variance of perceived corruption across countries.

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