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Dynamic interconnections between corruption and economic growth

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Abstract

This study examines the dynamic relationship between corruption and economic growth, focusing on the transmission mechanisms and contagion channels through which shocks in one country influence economic performance and corruption perceptions in others. Using data from Gross Domestic Product (GDP) and the Corruption Perception Index (CPI), we employ a coupled vector autoregressive model to capture the interactions between these variables. The results show that corruption and economic growth are interdependent across countries, with significant spillovers through trade and investment channels. By integrating graph theory and Granger causality, we build a network of interconnections that illustrates how corruption dynamics in one country can influence others, contributing to the "grease vs. sand" debate. These findings provide insights for designing policies that promote transparency and sustainable economic development.

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1. Introduction

The relationship between corruption and economic performance has been the subject of an extensive debate in the literature, often framed in terms of whether corruption acts as a form of “grease” or “sand” in the wheels of the economy. On the one hand, corruption has been argued to facilitate economic activity by allowing firms to circumvent burdensome regulations and rigid institutions (the “grease” view). On the other hand, a large body of work emphasizes that corruption discourages entrepreneurship, encourages inefficient business practices, reduces investment, and ultimately hinders long-term growth (the “sand” view). Seminal contributions Mauro (1995); Murphy et al. (1991, 1993); Svensson (2005), as well as more recent evidence Arbex et al. (2025); Blackburn and Powell (2011), have documented these contrasting channels, highlighting the complex and context-dependent nature of the corruption–growth nexus. Most of the empirical literature, however, has focused on identifying average or long-run relationships between corruption and output levels, often treating corruption as a static determinant of growth. What remains less understood are the dynamic, directional, and cross-country spillovers that may arise between corruption perceptions and economic activity. In particular, it is unclear how corruption shocks in one country propagate to others, how output fluctuations influence corruption perceptions over time, and whether such interdependencies reinforce or mitigate the traditional “grease vs sand” mechanisms. This paper contributes to filling this gap by embedding output and corruption into a coupled VAR framework and constructing multilayer, signed, directed networks that map predictive spillovers within and across countries. By doing so, we complement the existing literature with a comparative and dynamic perspective that highlights not only whether corruption matters for growth, but also how and where such effects propagate across interconnected economies.

Beyond this classical debate, an essential dimension concerns how corruption is measured and compared across countries. In this regard, the Corruption Perceptions Index (CPI) has become the most widely used benchmark, providing a consistent cross-country metric that enables empirical analysis of the corruption–growth nexus. In the economic sphere, growth and economic activity can be severely impacted by corruption, as it not only discourages foreign investment but also distorts resource allocation, leading to economic inefficiencies Lambsdorff (2003). However, some studies generate controversy by suggesting that, in certain contexts, corruption can have temporary effects that appear to enhance economic activity Aldana Umaña et al. (2019); Bigio and Ramírez-Rondán (2006). These effects include the acceleration of bureaucratic procedures, attracting investors looking to bypass strict regulations, or the redistribution of resources benefiting specific economic groups Al-Sadig (2009); Dimant and Tosato (2018). Nonetheless, these short-term benefits may entail negative long-term consequences, such as the spread of corruption, increased inequality, economic inefficiency, and loss of trust in institutions Fernand Desfrancois and Pastás Gutiérrez (2022). These diverse perspectives on the relationship between corruption and economic growth suggest a highly complex relationship, with aspects that have yet to be fully understood. Motivated by these uncertainties, we aim to understand the dynamic relationship between corruption and economic growth. We chose to approach the problem as a complex system composed of agents—in this case, countries—that interact through trade and political links. Each agent in the system has an economic performance and a corruption index, both of which vary over time. As is common in complex systems theory, we use both time series to reconstruct the structure that links the agents in the system. With this goal in mind, and inspired by Avdjiev et al. (2019), we propose a system of stochastic dynamic equations to model the dependency between these two time series. Additionally, based on these equations and using graph theory and Granger causality criteria, we demonstrate how to estimate the structure that describes the dynamic relationship between corruption and economic growth.

To measure the corruption of each agent, we chose the Corruption Perceptions Index (CPI), a measurement scale developed by Transparency International[1], which assesses the perception of corruption in a country's public sector, based on expert evaluations and surveys that provide an annual score. Data collection for the CPI began in 2012, and its consistency has been widely recognized by researchers, businesses, and governments as a key tool for measuring corruption. On the other hand, to measure economic growth, we selected the Gross Domestic Product (GDP), which is an economic measure representing the total monetary value of the final goods and services produced within a nation's borders during a specific period Cayo Vega (2021). This is a widely used indicator to measure a country's economic performance and allows for periodic evaluation of economic activity. Due to measurement limitations, both in availability and quality of data, especially for the CPI, we opted to select a subset of thirteen countries to implement our model and thus construct the structure of connections. These thirteen countries were selected based on criteria of economic and political representativeness, either global or regional, see Table 1.

We believe that the connection structure between corruption and economic growth, which naturally arises from our model, can be used as a valuable tool for economic and political analysis. Our approach aims to capture the complexities and multifaceted interactions between these variables. In this way, our proposal can not only help gain a deeper understanding of the effects and causes of corruption on the economy but also serve as a support in the design and implementation of policies that promote transparency and the fight against corruption. Additionally, our model is simple to implement and relies on parameters that are easily estimated using available, reliable, and open-access data.

In summary, this paper contributes to the corruption–growth literature by moving beyond average cross-country correlations and focusing instead on the dynamic and directional spillovers that link output and corruption perceptions both within and across countries. Using a coupled VAR framework, we construct multilayer, signed, directed networks that map how shocks propagate between GDP and CPI. This approach complements the traditional "grease vs sand" debate Arbex et al. (2025); Blackburn and Powell (2011); Mauro (1995); Murphy et al. (1991, 1993); Svensson (2005) by providing a comparative and dynamic perspective: not only whether corruption matters for growth, but also how and where such effects spread across interconnected economies. Our results therefore offer a novel empirical mapping of predictive spillovers that enriches the understanding of corruption as either grease or sand in the wheels of economic performance.

[1]`https://www.transparency.org/es/press/cpi2023-corruption-perceptions-index ex-weakening-justice-systems-leave-corruption-unchecked`

2. Economic intuition and channels

This section provides the economic intuition underlying our empirical analysis. While the Introduction has situated the paper within the corruption–growth literature and the "grease vs sand" debate, here we outline the specific mechanisms through which corruption and output may affect each other, as well as how these dynamics can propagate across countries. We also provide an intuitive description of the multilayer network representation, which will be formally defined in Section 3.

Corruption to GDP. Several well-established channels suggest that corruption negatively affects economic activity. It increases transaction costs and uncertainty, discourages foreign direct investment, distorts the allocation of talent away from productive activities, and reduces incentives for innovation Blackburn and Powell (2011); Mauro (1995). These mechanisms are consistent with the "sand" view, where corruption undermines long-run growth. At the same time, in contexts of heavy regulation and administrative bottlenecks, corruption can temporarily act as a "grease" that expedites transactions, allowing firms to overcome rigidities Murphy et al. (1991, 1993); Svensson (2005). In our empirical framework, these contrasting effects are reflected in the sign of the directed edge from CPI to GDP: a negative link indicates sand-type spillovers, while a positive link is consistent with grease-type dynamics.

GDP to Corruption. The reverse direction is equally important. Higher GDP can reduce corruption through increased fiscal revenues that strengthen monitoring capacity, better enforcement of contracts, and greater social demand for institutional quality as societies become wealthier Treisman (2000). Conversely, economic growth can also increase the scope for rent-seeking by generating larger economic rents, reinforcing patronage networks, or fueling political pressures that erode accountability Aidt (2009). Our VAR-based networks allow us to empirically disentangle these competing mechanisms: negative GDP$\rightarrow$CPI edges correspond to growth-induced reductions in corruption, while positive edges capture growth-driven increases in rent-seeking opportunities.

Cross-country transmission. Beyond domestic interactions, there are plausible international channels through which corruption and GDP dynamics may spill over across borders. Trade and Foreign Direct Investment (FDI) linkages can transmit shocks from one country to another, either by diffusing corruption-related costs along supply chains or by amplifying productivity shocks across partners. Multinational firms and global value chains may also propagate institutional practices—both positive and negative—across countries. Furthermore, perceptions of corruption are shaped by cross-border information flows, media coverage, and policy diffusion among neighboring economies, see Drury et al. (2006). In our multilayer representation, directed edges across countries capture these predictive spillovers, with their sign indicating whether the propagation amplifies or mitigates the corruption–growth nexus.

Connecting mechanisms to the empirical framework. By explicitly mapping these channels, our approach goes beyond a purely statistical exercise. The coupled VAR identifies dynamic predictive relations, and the multilayer network representation with signed edges provides an interpretable structure that reflects the economic mechanisms described above. Positive spillovers can be understood as grease-type propagation, while negative spillovers correspond to sand-type dynamics. Similarly, GDP$\rightarrow$CPI edges help assess whether economic growth strengthens institutions or fosters rent-seeking. Cross-country links capture how domestic shocks are transmitted internationally through economic and informational interdependence. This framework thus allows us to embed classical economic intuitions into a dynamic, quantitative setting, making the empirical results directly interpretable in terms of well-established theoretical hypotheses.

3. Methodology

3.1. Identification strategy

Our identification strategy builds upon the assumption that corruption and GDP are simultaneously determined, but the effect of one on the other is not instantaneous. The model structure allows for feedback in both directions between GDP and CPI, and the identification of these feedback effects is achieved by assuming contemporaneous exogeneity of the structural shocks. In other words, while the shocks to GDP and corruption are contemporaneously correlated, we assume that they are independent from each other, ensuring that we can disentangle the effects of each shock. Economic shocks are defined as the residuals (innovations) from the VAR model, and these shocks are orthogonal to the past values of both GDP and CPI. These innovations represent unpredicted, exogenous disturbances that affect both variables simultaneously. Specifically, we separate the shocks into two types:

- Growth/Productivity shocks, which capture unexpected changes in economic activity or productivity that affect GDP.
- Institutional/Political shocks, which reflect unforeseen changes in corruption levels that are independent of past economic performance.

By separating these shocks, we allow for a clear distinction between the corruption-driven shocks (which might increase corruption levels) and GDP-driven shocks (which might influence institutional quality and corruption). These shocks are treated as independent sources of variation that allow us to identify the feedback effects between GDP and corruption. The formal specification of the VAR model, which operationalizes the identification strategy discussed here, is presented in the next section. Specifically, the VAR model allows us to estimate the dynamic relationships between GDP and CPI, capturing both the bidirectional feedback and the exogenous shocks. The identification strategy described here informs the structure of the VAR, where the innovations in GDP and CPI are treated as independent sources of variation that drive the dynamic interactions.

3.2. Model Formulation

Let $\mathbf{x}_t = (x_t^1, \dots, x_t^{13})$ and $\mathbf{y}_t = (y_t^1, \dots, y_t^{13})$ be vectors containing the values of the GDP and CPI variables corresponding to the thirteen countries listed in Table 1, assumed at time

t. We assume that the joint process $(\mathbf{x}_t, \mathbf{y}_t)$ is governed by the system of stochastic equations

$$
\begin{cases}
\mathbf{x}_t &= \mathbf{b} + \sum_{s=1}^{p} \Phi(s)\,\mathbf{x}_{t-s} + \sum_{s=1}^{p} \Pi(s)\,\mathbf{y}_{t-s} + \xi_t \\
\mathbf{y}_t &= \mathbf{c} + \sum_{s=1}^{p} \Psi(s)\,\mathbf{y}_{t-s} + \sum_{s=1}^{p} \Gamma(s)\,\mathbf{x}_{t-s} + \zeta_t\,,
\end{cases}
\tag{1}
$$

where $\xi_t \overset{i.i.d}{\sim} N(0,\Omega)$, $\zeta_t \overset{i.i.d}{\sim} N(0,\Sigma)$ and p is the maximum number of lags. The parameters $\mathbf{b}, \mathbf{c} \in \mathbb{R}^{13}$ are vectors containing the model's intercepts. Additionally, we assume that the joint process $(\mathbf{x}_t, \mathbf{y}_t)$ is observed over T periods. The total parameters of the model are

$$
\Theta = \left(\mathbf{b}, \mathbf{c}, \left\{\Phi(s)\right\}_{s=1}^{p}, \left\{\Pi(s)\right\}_{s=1}^{p}, \left\{\Psi(s)\right\}_{s=1}^{p}, \left\{\Gamma(s)\right\}_{s=1}^{p}, \Omega, \Sigma\right) \tag{2}
$$

which vary freely, such that $\Omega, \Sigma \in \mathbb{R}^{13\times 13}$ are positive definite matrices. The estimation of the parameters Θ is performed by maximizing the conditional likelihood function associated with the model; for more details, see Hamilton (2020); Lütkepohl (2005). Note that the first and second equation in model (1) can be seen as a vector autoregressive model with exogenous variables, where the response variable of one is the exogenous variable of the other. Therefore, our model can be viewed as two coupled vector autoregressive models.

Our model, formulated in Equation (1), describes the dynamic interaction relationships between GDP and CPI, enabling the simultaneous identification of contagion effects of corruption and the spread of economic shocks. For example, concerning the first line of Equation (1), the matrix $\Phi(s)$ describes the s-th lagged endogenous shock of GDP for GDP, and the matrix $\Pi(s)$ describes the s-th lagged effect of CPI for GDP. Similarly, concerning the second line of Equation (1), the matrix $\Psi(s)$ describes the s-th lagged endogenous effect of CPI for CPI, and the matrix $\Gamma(s)$ describes the s-th lagged shock of GDP for CPI.

As shown later, this structure of coupled dynamics enables the identification of patterns of economic and political interdependence, patterns that reveal how economic-political fluctuations in one country can influence others, both in terms of corruption perception and economic growth.

In this work, we model the interconnection networks between corruption perception and economic growth through four directed, weighted, and acyclic graphs, which are associated with the dynamic relationships described in Equation (1). In these graphs, countries are represented by vertices whose interactions are represented by the edges of these graphs. To provide a precise description of the structure of these graphs, we introduce the concept of *Weighted Adjacency Matrices* associated with each graph, see Harary (1962). These matrices use statistically significant lagged effects and shocks to establish connections between the edges, a criterion widely known as Granger causality Granger (1969). Therefore, the elements of the adjacency matrices associated with the first line of Equation (1) are defined as

$$\mathbb{G}_{\Phi}(i,j) = \begin{cases} \sum_{s=1}^{p} \Phi_{ij}(s), & \text{if } x_t^j \longrightarrow x_t^i\,, \\ 0, & \text{otherwise,} \end{cases} \tag{3}$$

$$\mathbb{G}_{\Pi}(i,k) = \begin{cases} \sum_{s=1}^{p} \Pi_{ik}(s), & \text{if } y_t^k \longrightarrow x_t^i\,, \\ 0, & \text{otherwise,} \end{cases} \tag{4}$$

where the symbol "$\longrightarrow$" denotes the existence of a causal relationship in the Granger sense. The element $\mathbb{G}_{\Phi}(i,j)$ measures the total sum of the lagged shocks of the GDP of country j on the GDP of country i, while $\mathbb{G}_{\Pi}(i,k)$ measures the total sum of the lagged effects of the CPI of country k on the GDP of country i. Therefore, the adjacency matrices $\mathbb{G}_{\Phi}$ and $\mathbb{G}_{\Pi}$ represent how the economic and political fluctuations of one country affect others. Similarly, the elements of the matrices $\mathbb{G}_{\Psi}$ and $\mathbb{G}_{\Gamma}$ associated with the second line of Equation (1) are defined, capturing the lagged effects and shocks of the CPI and GDP on the CPI.

$$\mathbb{G}_{\Psi}(i,j) = \begin{cases} \sum_{s=1}^{p} \Psi_{ij}(s), & \text{if } y_t^j \longrightarrow y_t^i\,, \\ 0, & \text{otherwise,} \end{cases} \tag{5}$$

$$\mathbb{G}_{\Gamma}(i,k) = \begin{cases} \sum_{s=1}^{p} \Gamma_{ik}(s), & \text{if } x_t^k \longrightarrow y_t^i\,, \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

Analogous to the previous case, $\mathbb{G}_{\Psi}(i,j)$ measures the total sum of the lagged effects of the CPI corresponding to country j on the CPI corresponding to country i, capturing how changes in corruption perception in one country can influence the perception of corruption in another country. Similarly, $\mathbb{G}_{\Gamma}(i,k)$ represents the total sum of the lagged shocks of the GDP of country k on the CPI of country i, allowing the model to incorporate the fact that the economic growth of one country can impact the corruption perception of another country. Therefore, we can say that all the information about the interconnection network between corruption and economic growth described by our model is fully characterized by the matrices $\mathbb{G}_{\Phi}, \mathbb{G}_{\Pi}, \mathbb{G}_{\Psi}$, and $\mathbb{G}_{\Gamma}$.

3.2.1. Estimation of the interconnection network

Estimating the network is equivalent to obtaining the estimators $\hat{\mathbb{G}}_{\Phi}$, $\hat{\mathbb{G}}_{\Pi}$, $\hat{\mathbb{G}}_{\Psi}$ and $\hat{\mathbb{G}}_{\Gamma}$. There are various methods for estimating these adjacency matrices; see, for example, George et al. (2008); Seth (2007); Tibshirani (1996); Zou and Feng (2009). In this study, we opted to use criteria based on conditional Granger causality, as outlined in Ding et al. (2006), which could be considered a multivariate extension of the bivariate arguments initially presented in Granger (1969).

Granger causalities are identified by fitting the vector autoregressive models in the first and second lines of (1). For example, we say that x_t^j causes x_t^i, denoted by $x_t^j \longrightarrow x_t^i$, if at least one of the elements $\Phi_{ij}(s)$ for $s = 1, \ldots, p$ is significantly different from zero. This can be tested empirically by conducting the F-test of the hypothesis

$$H_0 : \Phi_{ij}(1) = \ldots = \Phi_{ij}(p) = 0 \quad \Longrightarrow \hat{\mathbb{G}}_\Phi(i,j) = 0\,,$$
$$H_1 : \forall s = 1, \ldots, p,\ \exists \Phi_{ij}(s) \neq 0 \quad \Longrightarrow \hat{\mathbb{G}}_\Phi(i,j) = \sum_{s=1}^{p} \hat{\Phi}_{ij}(s)\,,$$

where $\hat{\Phi}_{ij}(s)$ is the (i, j)-th element of the estimator of $\Phi(s)$ in Equation (1). The order p is set using standard model selection criteria, such as the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC); see Hamilton (2020); Lütkepohl (2005). Similarly, we obtain the estimators $\hat{\mathbb{G}}_\Pi, \hat{\mathbb{G}}_\Psi$, and $\hat{\mathbb{G}}_\Gamma$ by conducting hypothesis tests on the elements of $\Pi(s)$, $\Psi(s)$, and $\Gamma(s)$ for $s = 1, \ldots, p$. The estimators $\hat{\mathbb{G}}_\Phi, \hat{\mathbb{G}}_\Pi, \hat{\mathbb{G}}_\Psi$, and $\hat{\mathbb{G}}_\Gamma$ are presented in 2, 3, 4, 5.

4. Dataset

For this study, we considered a subgroup consisting of thirteen nations, selected for their economic and political relevance at the global or regional level. This group includes France (FRA), Italy (ITA), Japan (JAP), Spain (SPA), the United Kingdom (UK), Germany (GER), Canada (CAN), India (IND), Brazil (BRA), Mexico (MEX), Chile (CHI), Peru (PER), and the United States (USA). For better organization, we have grouped the countries into three major groups: *South America*, *Europe*, and *USA* & *Others*, see Table 1.

We relied on three main data sources to implement the dataset used in this study. To obtain GDP data for the total set of considered countries, denoted in (1) as $\mathbf{x}_t$, we used data provided by the World Bank [2]. Regarding the CPI data for the total set of considered countries, denoted in (1) as $\mathbf{y}_t$, we used data provided by the Transparency International portal[3]. It is worth mentioning that the original data frequency provided by the Transparency International portal is annual, unlike the data provided by the World Bank, which is quarterly. Therefore, concerning GDP data, we extracted data from the fourth quarter of 2012 to the fourth quarter of 2023, and concerning CPI data, we extracted annual data from 2012 to 2023. Subsequently, as part of the data processing and to obtain a common sampling frequency for both variables, we performed linear interpolations to generate quarterly CPI data. We acknowledge that the reliance on interpolated CPI data and short time series may raise concerns regarding the robustness of our results, particularly for Granger causality inference. However, despite these limitations, we have conducted several robustness checks within the available dataset. These include rolling window tests and subsample sensitivity analyses, which show that the main relationships identified in the paper remain stable and consistent across different time periods and data subsets. Thus, while the use of interpolated data presents inherent challenges, we believe the results are robust and reliable within the context of the available data.

Once the information described above was extracted and preprocessed, we unified it into

[2] https://datos.bancomundial.org/
[3] https://www.transparency.org/es/press/cpi2023-corruption- perceptions-index

a dataset that we can denote as

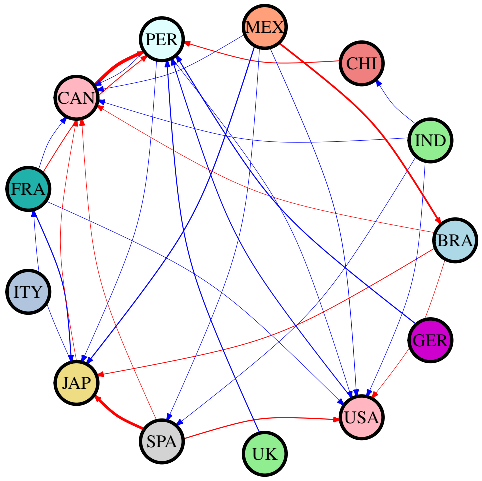
$$\mathcal{D} = \big\{(\mathbf{x}_t, \mathbf{y}_t),\, t = 1, \dots, T\big\}, \tag{7}$$

where $T = 45$ quarters. Therefore, our database consists of observations of the joint process $(\mathbf{x}_t, \mathbf{y}_t)$ over 45 quarters. The plots of the series $\{\mathbf{x}_t\}_{t=1}^{T}$ and $\{\mathbf{y}_t\}_{t=1}^{T}$, organized by groups of countries, are presented in Figure 2, Figure 3, and Figure 4.

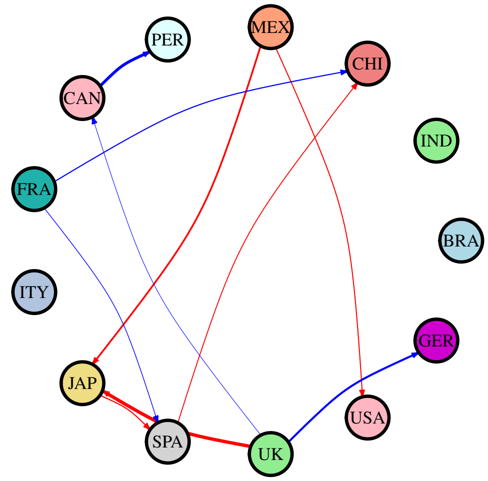
5. Results

Since the first line in Equation (1), as well as the second line in Equation (1), can be viewed in isolation as a vector autoregressive model with exogenous variables, this allows us to use standard methods based on maximizing the conditional likelihood to estimate their parameters; see Hamilton (2020); Lütkepohl (2005). Therefore, using the dataset $\mathcal{D}$, together with standard procedures, we estimate the parameters Θ defined in (2). It is worth mentioning that, based on the model selection criteria described in Section 3, we set an optimal value of $p = 1$. Additionally, satisfactory structural stability tests were performed on both vector autoregressions using the OLS-CUSUM method and inverse polynomial root analysis. Subsequently, we obtain the estimators of the adjacency matrices $\hat{\mathbb{G}}_\Phi, \hat{\mathbb{G}}_\Pi, \hat{\mathbb{G}}_\Psi$, and $\hat{\mathbb{G}}_\Gamma$ using the procedures described in Section 3. Finally, using these estimators, we construct their associated graphs, which are shown below.

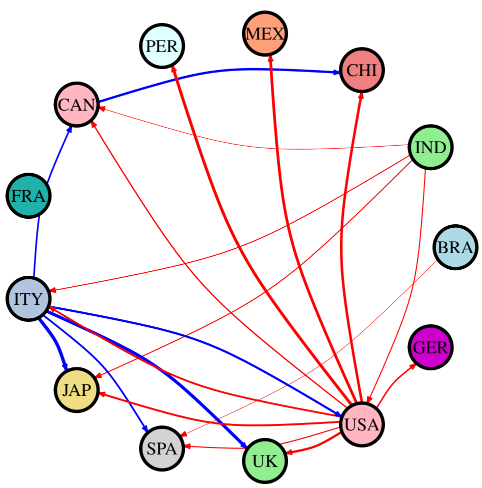
The graph generated from the matrix $\hat{\mathbb{G}}_\Phi$ confirms the expected hypothesis that the GDP of one country influences that of other countries, see Figure 1a. In this context, the edges connecting the nodes reflect the effect that the GDP of one country has on the GDP of another. In this way, the graph facilitates the identification of possible economic and trade relationships. Similarly, the graph generated from the matrix $\hat{\mathbb{G}}_\Pi$ shows the interactions between the CPI and the GDP of various countries, indicating that the level of corruption in one country influences the economic activity of another, see Figure 1b. The edges connect countries where the CPI of one has a significant effect on the GDP of the other, revealing important causal relationships that show how corruption in one nation can affect, positively or negatively, economic growth in another. On the other hand, the graph represented by the matrix $\hat{\mathbb{G}}_\Psi$ provides a detailed visualization of the interactions between the CPIs of different countries, illustrating how the level of corruption perception in one country influences that of another, see Figure 1c. In this context, the edges connecting the nodes reflect the effect that the CPI of one country has on the CPI of another, facilitating the identification of possible relationships and patterns of interdependence regarding corruption perception between nations. Finally, the graph generated from the matrix $\hat{\mathbb{G}}_\Gamma$ visualizes the interactions between the GDP and the CPI of different countries, showing how the economic activity of one country can influence the corruption perception in another, see Figure 1d. The edges connect cases where the GDP of one country affects the CPI of another, facilitating the identification of causal relationships between economic growth and corruption. This analysis provides a deeper insight into how economic prosperity can impact transparency at the international level.



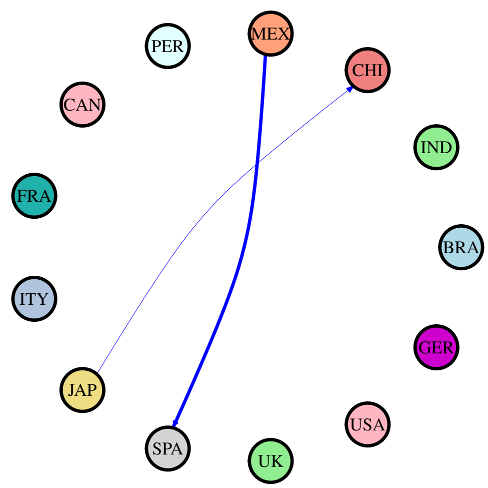
(a) Graph associated with $\hat{\mathbb{G}}_{\Phi}$



(b) Graph associated with $\hat{\mathbb{G}}_{\Pi}$



(c) Graph associated with $\hat{\mathbb{G}}_{\Psi}$



(d) Graph associated with $\hat{\mathbb{G}}_{\Gamma}$

Figure 1: (a) The graph associated with $\hat{\mathbb{G}}_{\Phi}$ illustrates the relationship between the GDP of one country and that of others (blue arrows indicate direct positive effects, red arrows inverse effects). (b) The graph associated with $\hat{\mathbb{G}}_{\Pi}$ depicts the influence of a country's CPI on the GDP of other countries (blue arrows indicate direct effects, red arrows inverse effects). (c) The graph associated with $\hat{\mathbb{G}}_{\Psi}$ shows the influence of a country's CPI on the CPI of other countries (blue arrows indicate direct effects, red arrows inverse effects). (d) The graph associated with $\hat{\mathbb{G}}_{\Gamma}$ illustrates the influence of a country's GDP on the CPI of other countries (blue arrows indicate direct effects, red arrows inverse effects). For a more detailed assessment of the degree of connectivity and structural properties among these graphs, refer to the network metrics summarized in Table 6, which include measures such as centrality, density, and clustering coefficients

6. Transmission Mechanisms and Contagion Channels between Countries: Analysis of Dynamic Effects

In this section, we explore the transmission mechanisms and contagion channels that arise from the results obtained in the analysis of the dynamic relationships between Gross Domestic Product (GDP) and the Corruption Perceptions Index (CPI) of the countries studied. The results, represented through the graphs generated from the causality matrices $\hat{\mathbb{G}}_{\Phi}$, $\hat{\mathbb{G}}_{\Pi}$, $\hat{\mathbb{G}}_{\Psi}$, and $\hat{\mathbb{G}}_{\Gamma}$, allow us to understand how economic and corruption shocks in one country can propagate to others, generating significant effects on their economic growth and corruption perceptions. The results presented in the previous section show that the effects of corruption and economic growth are not confined to a single economy but spread through international channels activated by economic and political interdependence between countries. Specifically, the propagation of shocks in one country can lead to changes in both the perception of corruption and the economic performance of other countries.

In terms of corruption contagion, the results from the matrix $\hat{\mathbb{G}}_{\Pi}$ show that corruption shocks in one country can have direct effects on the GDPs of other countries. This suggests that the negative effects of corruption can spread through trade relations and foreign direct investment (FDI) networks. For example, increased corruption in major economies like the United States or Germany can lead to instability in more vulnerable economies, affecting their growth and corruption perception. However, the perception of corruption in more stable economies, such as Japan or Canada, also affects the economic stability of countries dependent on them for trade and investment. The analysis shows that countries like Peru and Chile are directly influenced by larger economies like the United States and Spain, which may be explained by transnational information flows and media effects that propagate corruption perceptions regionally. Regarding economic growth contagion, the results from the matrix $\hat{\mathbb{G}}_{\Phi}$ demonstrate that growth shocks in leading countries such as the U.S., Japan, and Germany directly influence the economic performance of smaller and more dependent economies. This shows how growth shocks in large economies are transmitted to smaller economies through trade and investment networks. At the same time, there are inverse effects in countries with political or economic instability. For example, in countries like Peru and Mexico, economic growth does not always have a positive effect on corruption. The matrices $\hat{\mathbb{G}}_{\Gamma}$ show that growth shocks can increase rent-seeking opportunities and reinforce patronage networks, which in turn leads to a high corruption perception despite positive GDP growth.

These analysis allows us to integrate traditional theories of corruption, particularly the debate between corruption as "grease" or "sand" in the economy. In countries where corruption facilitates transaction flows or helps overcome bureaucratic rigidities, corruption acts as "grease", making transactions faster and less costly. This is the case in some countries with high corruption but more open economies to foreign direct investments. However, in many countries with high levels of corruption, the "sand" effect dominates, as corruption generates inefficiencies, distorts resource allocation, and stifles investment in key sectors for sustainable growth. Finally, the dynamic analysis of the relationship between GDP and CPI shows that both economic and corruption shocks do not only affect the directly involved countries but also propagate through a global network. The multilayer networks, visualized in the graphs associated with matrices $\hat{\mathbb{G}}_\Phi$, $\hat{\mathbb{G}}_\Pi$, $\hat{\mathbb{G}}_\Psi$, and $\hat{\mathbb{G}}_\Gamma$, demonstrate how interconnected economies are and how shocks in one country can have economic and political repercussions in others. These results suggest that the fight against corruption must be global and coordinated, as the effects of corruption and growth shocks do not respect national borders. Transnational policies promoting transparency and governance are essential to mitigate the negative effects of corruption on global economic growth, and this study provides a quantitative framework to assess the impact of such policies.

7. Conclusions

This study contributes to the literature on the relationship between corruption and economic growth by going beyond the traditional approach that identifies average correlations between the two. Using a multilayer approach and Granger causality analysis, we have shown how corruption and economic growth shocks not only affect economies in isolation but also propagate through international channels, generating transnational repercussions. The transmission mechanisms and contagion channels identified in Chapter 6 have been crucial to understanding how interconnected economies influence each other. The results demonstrate that key economies, such as the United States and Germany, have a direct impact on other economies through trade networks and foreign investments, amplifying both the effects of corruption and economic growth. The study also provides a dynamic perspective in the debate on whether corruption acts as "grease" or "sand" in the economy. While in certain contexts, corruption acts as "grease," accelerating certain economic processes, in many others, the "sand" effect predominates, where corruption distorts markets and hinders long-term growth. The contagion channels that connect these dynamics between countries emphasize the need to consider transnational effects in the design of economic policies.

Finally, integrating the findings from Chapter 6, we conclude that the fight against corruption cannot be limited to national policies. The global effects of corruption and economic growth require a coordinated, global approach to mitigate their repercussions. Transparency and governance policies must be implemented not only at the national level but also through international cooperation to ensure a positive impact on global economic stability. This study offers a valuable quantitative framework for formulating policies that promote international cooperation in the fight against corruption and foster sustainable economic growth across interconnected economies.

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Appendices

South America		Europe		USA & Others	
Country	**Label**	**Country**	**Label**	**Country**	**Label**
Brazil	BRA	Germany	GER	Canada	CAN
Chile	CHI	Spain	SPA	United States	USA
Peru	PER	France	FRA	India	IND
		Italy	ITA	Japan	JAP
		United Kingdom	UK	Mexico	MEX

Table 1: List of selected countries for analysis, grouped into three groups: South America, Europe, and USA & Others

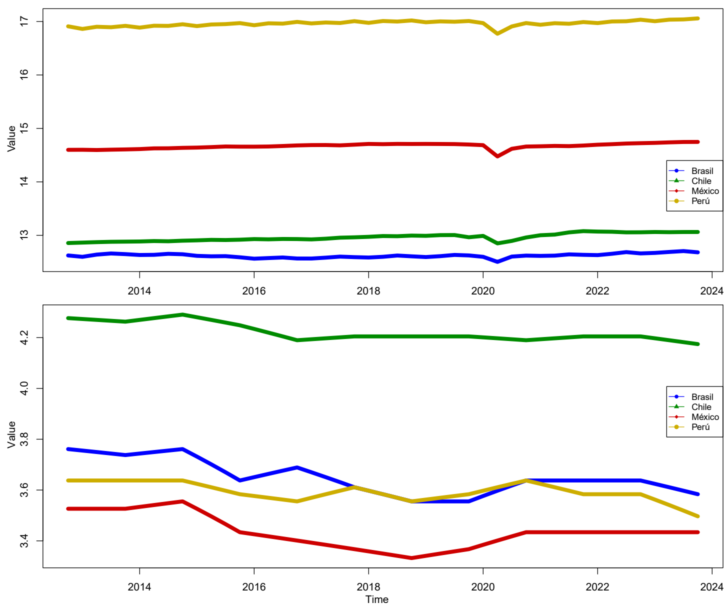

Figure 2: Series charts for the South America group. The upper chart shows the sampled GDP series, while the lower chart shows the sampled CPI series.

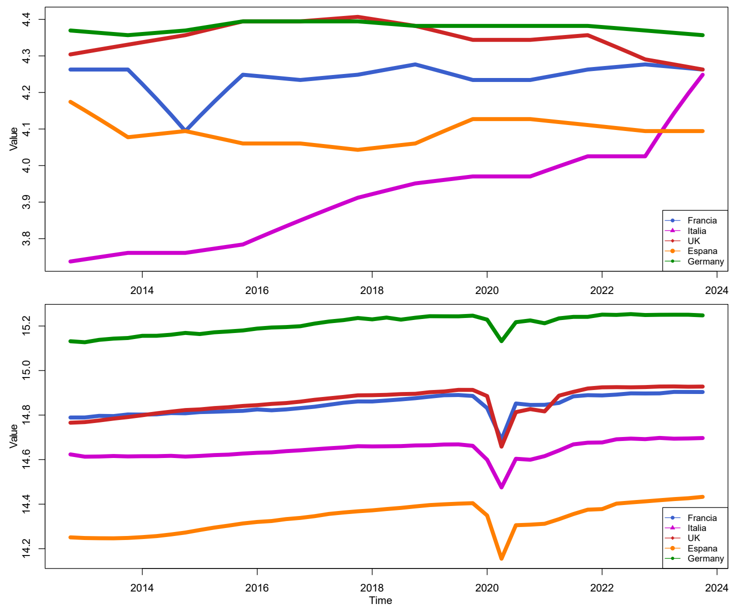

Figure 3: Series charts for the Europe group. The upper chart shows the sampled GDP series, while the lower chart shows the sampled CPI series.

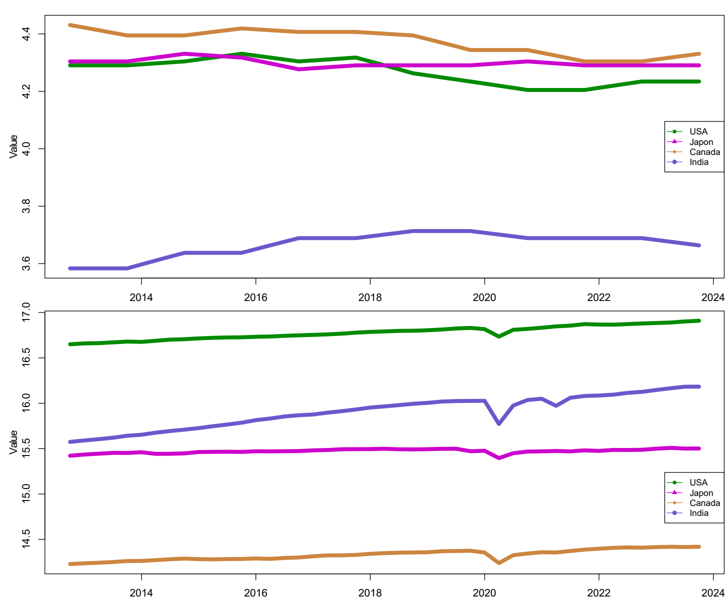

Figure 4: Series plots for the USA & Others group. The top plot displays the sampled GDP series, while the bottom plot shows the sampled CPI series.

GDP / GDP	BRA	IND	CHI	MEX	PER	GER	CAN	FRA	ITA	JAP	SPA	UK	USA
BRA	0	0	0	0	0	-2.75	0	0	-14.75	0	0	-6.82	0
IND	0	0	3.37	0	0	2.02	0	0	0	3.57	0	3.78	0
CHI	0	0	0	0	-17.40	0	0	0	0	0	0	0	0
MEX	-33.54	0	0	0	0	4.73	0	0	20.71	5.66	0	11.24	0
PER	0	0	0	0	0	0.57	0	0	3.72	0	0	1.64	0
GER	0	0	0	0	-64.86	0	0	0	0	0	0	0	0
CAN	0	0	0	0	-15.96	2.96	0	0	20.37	0	0	8.53	0
FRA	0	0	0	0	0	0	0	0	0	0	0	0	0
ITA	0	0	0	0	0	-0.07	0.17	0	0	0	0	0	0
JAP	0	0	0	0	0	-7.49	0	0	-52.53	0	0	-20.92	0
SPA	0	0	0	0	19.02	0	0	0	0	0	0	0	0
UK	0	0	0	0	17.48	0	0	0	0	0	0	0	0
USA	0	0	0	0	20.41	0	0	0	0	0	0	0	0

Table 2: Matrix $\hat{\mathbb{G}}_{\Phi}$.

GDP / CPI	BRA	IND	CHI	MEX	PER	GER	CAN	FRA	ITA	JAP	SPA	UK	USA
BRA	0	0	0	0	0	0	0	0	0	0	0	0	0
IND	0	0	0	0	0	0	0	0	0	0	0	0	0
CHI	0	0	0	0	0	0	0	0	0	0	0	0	0
MEX	0	0	0	0	0	0	0	0	-0.74	0	0	-0.43	0
PER	0	0	0	0	0	0	0	0	0	0	0	0	0
GER	0	0	0	0	1.23	0	0	0	0	0	0	0	0
CAN	0	0	0.47	0	0	0	0	0	0	0.31	0	0	0
FRA	0	0	0	0	0	0	0	0	0	0	0	0	0
ITA	0	0	0	0	0	0	0	0	0	-0.47	0	0	0
JAP	0	0	-0.39	0	0	0	0	0	0	0	0	0	0
SPA	0	0	0	0	0	0.22	0	0	-1.41	0	0	0	0.87
UK	0	0	0	0	0	0	0	0	0	0	0	0	0
USA	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 3: Matrix $\hat{\mathbb{G}}_{\Pi}$.

CPI / CPI	BRA	IND	CHI	MEX	PER	GER	CAN	FRA	ITA	JAP	SPA	UK	USA
BRA	0	0	0	0	0	0	0	0	0	-0.39	0	0	0
IND	0	0	0	0	0	-0.48	0	-0.78	-0.82	0	0	-0.85	0
CHI	0	0	0	0	0	0	0	0	0	0	0	0	0
MEX	0	0	0	0	0	0	0	0	0	0	0	0	0
PER	0	0	0	0	0	0	0	0	0	0	0	0	0
GER	0	0	1.89	0	0	0	0	0	0	0	0	0	0
CAN	0	0	0	0	0	0	0	0	0	0	0	0	0
FRA	0	0	0	0	0	1.33	0	0	2.71	1.47	2.57	1.75	0
ITA	0	0	0	0	0	0	0	0	0	0	0	0	0
JAP	0	0	0	0	0	0	0	0	0	0	0	0	0
SPA	0	0	0	0	0	0	0	0	0	0	0	0	0
UK	0	0	-2.08	-2.24	-2.38	-1.06	0	-1.51	-1.56	-0.89	-1.85	0	-1.20
USA	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 4: Matrix $\hat{\mathbb{G}}_{\Psi}$.

CPI / GDP	BRA	IND	CHI	MEX	PER	GER	CAN	FRA	ITA	JAP	SPA	UK	USA
BRA	0	0	0	0	0	0	0	0	0	0	0	0	0
IND	0	0	0	0	0	0	0	0	0	0	0	0	0
CHI	0	0	0	0	0	0	0	0	0	0	0	0	0
MEX	0	0	0	0	0	0	0	0	0	19.71	0	0	0
PER	0	0	0	0	0	0	0	0	0	0	0	0	0
GER	0	0	0	0	0	0	0	0	0	0	0	0	0
CAN	0	0	0	0	0	0	0	0	0	0	0	0	0
FRA	0	0	0	0	0	0	0	0	0	0	0	0	0
ITA	0	0	0.76	0	0	0	0	0	0	0	0	0	0
JAP	0	0	0	0	0	0	0	0	0	0	0	0	0
SPA	0	0	0	0	0	0	0	0	0	0	0	0	0
UK	0	0	0	0	0	0	0	0	0	0	0	0	0
USA	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 5: Matrix $\hat{\mathbb{G}}_{\Gamma}$.

Country	$\mathbf{G}_\Phi$ (GDP → GDP)			$\mathbf{G}_\Pi$ (CPI → GDP)			$\mathbf{G}_\Psi$ (CPI → CPI)			$\mathbf{G}_\Gamma$ (GDP → CPI)		
	In	Out	Bet	In	Out	Bet	In	Out	Bet	In	Out	Bet
BRA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0
IND	3.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
CHI	17.4	0.0	0.0	0.5	0.0	0.0	1.9	0.0	0.0	0.8	0.0	0.0
MEX	0.0	54.3	0.0	0.0	1.2	0.0	0.0	0.0	0.0	19.7	0.0	0.0
PER	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
GER	64.9	2.8	0.0	1.2	0.0	0.0	1.3	0.0	0.0	0.0	0.0	0.0
CAN	16.0	3.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0
FRA	0.0	14.8	0.0	0.0	0.0	0.0	2.7	0.0	0.0	0.0	0.0	0.0
ITA	0.2	0.0	0.0	0.3	0.5	0.0	1.5	0.0	0.0	0.0	0.0	0.0
JAP	52.5	7.5	0.2	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
SPA	0.0	19.0	0.0	1.4	0.2	0.0	1.8	0.0	0.0	0.0	0.0	0.0
UK	0.0	17.5	0.0	0.0	0.0	0.0	0.0	10.3	0.5	0.0	0.0	0.0
USA	0.0	20.4	0.4	0.9	0.0	0.0	1.2	0.0	0.0	0.0	0.0	0.0

Table 6: Network Metrics (In-Degree, Out-Degree, Betweenness Centrality) for the interconnection graphs.