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The privatization-corruption relationship is nonlinear: Evidence from 1985-2022 data on telecommunications in 103 countries[+]

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Abstract

Using data on telecommunications from 1985 to 2022 in 103 countries, this article provides evidence of a robust nonlinear relationship between privatization and corruption showing that the latter has an inverted U-shape effect on the former. Using the Bayesian Corruption Index as a proxy for corruption, we find that the threshold beyond which higher levels of corruption do no longer foster privatization is slightly above 50% of the maximum value of this index. The complexity of the relationship between privatization and corruption points to the need to develop sophisticated strategies to effectively combat corruption, the negative effects of which on social welfare have been widely discussed in the literature.

Keywords: Privatization; Corruption; Telecommunications; Nonlinearity.
JEL classification codes: L33; D73; L96.

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1. Introduction

Considered the backbone of an economy, infrastructure is essential to economic development and the eradication of poverty. The lack of good infrastructure indeed imposes enormous costs on society.[1] In recent decades, many countries around the world have conducted structural reforms of their generally oversized and inefficient public utilities, and privatization has certainly been one of the most widely used tools. However, privatization decisions are made by government officials with potential private interests in reform policies and may therefore be subject to corruption.

Corruption is an obstacle to fighting poverty and sharing prosperity. Not only does it distort the allocation of resources, but it also harms the social contract by increasing inequality, undermining social cohesion, and eroding citizens' trust in governments and public institutions (World Bank, 2021). In low- and middle-income countries, lack of resources makes privatization particularly necessary for infrastructure financing but challenging as private capital often neglects this type of investment due to corruption concerns (Cane, 2021).[2]

The telecommunications sector has undergone significant reforms since the 1980s. These reforms were aimed at liberalizing the sector by introducing competition in the fixed and cellular segments coupled, in many cases, with the privatization of traditional fixed-line operators (Gasmi et al., 2012). Often, these changes also included establishing independent regulatory agencies and allowing for entry of foreign investors. These reforms have led to various market dynamics and the availability of data has made possible the analysis of their performance.[3]

Understanding the mechanism of privatization has been a long-lasting goal pursued by academics who, among other things, sought to analyze it within a positive theory of reform.[4] A prominent contribution is Laffont and Meleu (1999). The authors provide a

[1] In 2015, over 1.1 billion people worldwide still had no access to electricity, about 663 million lacked access to clean water, 2.4 billion did not have adequate sanitation, and 2.3 billion were not served by an all-weather road (Badré, 2015).

[2] For theoretical discussions of the costs and benefits of privatization, see Martimort (2006), Shibata and Nishihara (2011), and Schmidt (1996), among others.

[3] The literature has examined the impact of, among other factors, institutional quality on these reforms' performance (Belaid et al., 2009, Gasmi et al., 2009; Wallsten, 2001).

[4] Laffont (2005) is a great effort to analyze issues critical to development through the lens of the new regulatory economics. Chapter 3 of this book, that was still being typeset when Laffont sadly died in May 2004, is an enlightening synthetic work on a positive theory of privatization that builds on earlier contributions by, among others, Bennedsen (1996), Boycko et al. (1996), Laffont (1996), Laffont and Meleu (1999, 2001), Laffont and N'Guessan (1999), Shapiro and Willig (1990), and Shleifer and Vishny (1994). This book on regulation and development places great emphasis on the distributional consequences of public utilities reforms in developing countries. For a recent review of the empirical evidence on privatization with particular emphasis on important issues facing developing countries such as its distributional impacts, see Estrin and Pelletier (2018).

positive theory of privatization predicting that the (marginal) impact of corruption on privatization depends on the prevailing level of corruption itself, more specifically, the relationship between privatization and corruption is of an inverse-U shape. Our objective in this paper is to investigate the empirical validity of this nonlinearity property of the relationship between privatization and corruption, using a novel database on the telecommunications sector in 103 countries worldwide during the 1985-2022 period.

This paper is organized as follows. Section 2 reviews a selection of papers that analyzed the relationship between privatization and corruption, both theoretically and empirically, and which we consider close to our work. Section 3 presents the data collected and the results of a preliminary examination of their properties. Section 4 discusses the results of our econometric analysis of the data and section 5 concludes. The appendix provides some complementary material discussed in the main text.

2. Related work

In their positive theory of privatization, Laffont and Meleu (1999) show that the relationship between privatization and corruption is of an inverted U-shape form. They argue that at low levels of corruption, increasing levels of corruption should positively influence the decision to privatize a public firm as privatizations offer opportunities for politicians and other decision-makers to make private gains. On the other hand, for very high levels of corruption, those private gains cannot compensate for the loss of control and other rents politicians can extract from a state-owned firm. Thus, at high levels of corruption, increasing levels of corruption should negatively influence the decision to privatize, so the theory goes. This positive theory was synthesized by Laffont (2005), along with earlier contributions on the corruption-privatization relationship. Other scholars have actually examined the distribution implications of privatization, in particular the role of corruption.

Boycko et al. (1996) argue that the political benefits of public firms can greatly influence the decision to privatize them or not. The goal of the state could be to influence these companies to retain an inefficiently high level of employment to avoid higher levels of unemployment in society. Therefore, politicians may be reluctant to privatize as private companies are more costly to influence than public entities on which they have a direct influence. However, in such a case, corruption that leads to privatization can actually reduce inefficiency, as company management can bribe politicians to agree to lower employment.

Kaufmann and Siegelbaum (1997) also see a positive correlation between privatization and corruption in transition economies. However, in contrast to Laffont and Meleu (1999) and

Laffont (2005), these authors do not see corruption as the main motive for the decision to privatize. Instead, they argue that privatization is necessary to reform the economy, liberalize markets, combat hardening fiscal constraints, and reach a free and democratic system in the long-term. Corruption is thus only a negative by-product of privatization measures, not their cause. These authors argue that the openness and competitiveness of privatization processes are the key determinants of the degree of subsequent corruption in a country.

Along this line that puts forward the role of institutions, Molinari (2011) argues that the effect of corruption on the privatization process depends on the governance systems of countries.[5] In this author's theoretical model, managers of state-owned firms have private information on the possible efficiency gains of privatization and propose those efficiency increasing privatization opportunities to the government. In a good governance system, social welfare maximizing decision makers will agree with those privatizations to increase efficiency. However, in a bad governance system, decision makers will disagree and forego the benefits of privatization. A first effect of corruption is that its use by managers may be beneficial to social welfare as it influences decision makers to agree to the efficiency increasing privatizations that would otherwise not be undertaken. A second effect of corruption in Molinari's model is that it may lead to the selection of the most efficient producer as only the most capable to provide bribery.[6]

Martimort and Straub (2009) develop a theoretical model that predicts a positive correlation between privatization and corruption. However, they argue that the type of corruption also changes with the level of privatization. For low levels of privatization, corruption is used for soft money transfer schemes from state-owned enterprises to favored groups. In contrast, highly privatized entities use corruption to influence decision makers and regulators to allow higher prices and lower competition for the goods and services provided by the firm. So, Martimort and Straub (2009) predict a shift of the burden of corruption from taxpayers to consumers with the increase in the degree of privatization.

Bjorvatn and Søreide (2005) propose a theory implying that a privatization process leads to a high market concentration which in turn can cause an increase in corruption. The reasoning for this is that market power may give firms the financial strength needed to engage in corruption on a large scale. Additionally, bribes may be used to influence decision-makers

[5] See also Buia and Molinari (2012) and Molinari (2014) for contributions along these lines.

[6] Therefore, in contrast to Laffont and Meleu's (1999) theory, Molinari's (2011) allows us to infer that while the extent of corruption depends on the governance system of a country, the decision to privatize itself is exogenous to it.

to allow market concentration. In their empirical analysis, Bjorvatn and Søreide (2005) find that privatization in countries with highly corrupt governments results in more market concentration than in countries where governments are less corrupt. Hence, they also predict a positive correlation between privatization and corruption, in agreement with Kaufmann and Siegelbaum (1997). However, Bjorvatn and Søreide (2005) see, with market concentration, a different reason for the correlation between these two variables.

As we have seen, the interplay between privatization and corruption has been the subject of numerous theoretical papers. As more data have become available over the last decades, a fairly large empirical literature has developed in recent years. However, the influence of corruption on privatization that could be expected from most theoretical analyses proved to be opaquer in the data. In the following, we present a selection of most insightful papers that served as a basis for our own research.

Estache et al. (2009) examine the energy, telecommunications, and water sectors and show how corruption has negative effects on three dimensions of service performance, namely, quantity/access, quality, and cost. They also show that privatization and the setting of independent regulators did not always lead to better performance in the three dimensions. For their analysis, they use a dataset on 153 developing countries covering the period 1990-2002. Estache et al. (2009) obtained their results by regressing the three performance dimensions on a vector of reform policies, the corruption index published by the International Country Risk Guide, and some controls.

Gasmi and Recuero Virto (2010) analyze a dataset on the telecommunication industry in 86 developing countries during the period 1985-1999 by means of the System Generalized Method of Moments (SYS-GMM) for panel data. In their dynamic autoregressive model, privatization is a one-dimensional continuous variable while corruption and two population variables are the regressors. The corruption variable is modeled using a democracy index, namely, the IRIS data set by the University of Maryland. Based on various data sources, the privatization variable depicts the percentage of the assets of the state-owned enterprises that are sold to private investors. In contrast to the prediction of Laffont and Meleu's (1999) theory, Gasmi and Recuero Virto (2010) find a negative impact of corruption on privatization for all levels of corruption. However, these authors confirm that this impact is decreasing.

Koyuncu et al. (2010) hypothesize that privatization reduces corruption and attempt to test this hypothesis using both multivariate fixed time effect and multivariate random time effect models. To proxy their dependent variable, that is, corruption, these authors use three distinct corruption indices, namely the Freedom from Corruption index extracted from the

Heritage Foundation's 2009 Index of Economic Freedom, the Control of Corruption index from the Worldwide Governance Indicators database, and the Corruption Perception Index provided by Transparency International.[7]

Koyuncu et al. (2010) include privatization through six different variables which are privatization revenue (as percentage of GDP), private sector share in total employment, ratio of employment in publicly owned enterprises over total employment, private sector share in GDP, and two privatization indices provided by the European Bank for Reconstruction and Development. Possible endogeneity caused by a reverse causality between corruption and privatization is dealt with by using instrumental variables covering foreign direct investment, aid to the country, debt of the country, and a GPD deflator. For all the three corruption indicators, Koyuncu et al. (2010) find a significant negative impact of privatization on corruption.

Reinsberg et al. (2020) argue that the International Monetary Fund (IMF) can compel borrowing countries to implement anti-corruption policies that reduce corruption, but that other measures introduced at the same time, especially privatization of state-owned-enterprises, may open the door to opportunities for rent-seeking and reduce the ability of public institutions to rein corrupt behavior. To test this hypothesis, they use an instrumental variable regression technique to analyze a time-series-cross-sectional dataset on countries that have borrowed from the IMF from 1980 to 2014. The (dependent) corruption variable is constructed from the Control of Corruption Indicator provided by the International Country Risk Guide and the Corruption Perception Index provided by Transparency International. As the main predictor of this corruption variable, the authors use the number of binding conditions included in an IMF program requiring the privatization of state-owned enterprises. Reinsberg et al. (2020) then show that the privatization conditions and reforms mandated by the IMF increase corruption, which contradicts the expected effects of the policy recommendations.

In a contribution that is perhaps the closest to our paper, Peña Miguel and Cuadrado-Ballesteros (2019) give due attention to the causal relationship between privatization and corruption in both directions arguing that perceived corruption tends to be higher after privatization and that countries with higher perceived corruption are more likely to carry out privatization. They use a panel data set covering all privatizations in 25 European countries for

[7] Note that the very existence of several indicators for corruption, and more generally for institutional quality, has not been without raising questions among empirical economists. See Samadi and Alipourian (2021) for a discussion of this point.

the period 1995-2013, including western European countries such as France, the UK, and Italy and former eastern bloc/transition countries such as the Czech Republic, Latvia, and Lithuania.

In Peña Miguel and Cuadrado-Ballesteros's (2019) analysis, corruption is proxied by the Corruption Perception Index and the Bayesian Corruption Indicator made available by the Quality of Government (QoG) Institute. For privatization, they also use two indicators. The first indicator is the number of privatizations (partial and total) completed per year and per country. The second is the yearly total revenue from privatization as a percentage of GDP. In addition, the authors use the cumulative value of these two variables which they use in the perceived corruption regression only and not in the privatization regression. Fitting the data through ordinary least squares (OLS), Peña Miguel and Cuadrado-Ballesteros (2019) find, contrary to Laffont and Meleu (1999), that there is only a weakly significant and short-lasting effect of perceived corruption on privatization, while corruption increases strongly with both the number and value of privatizations.

A recent empirical piece on the relationship between corruption and privatization is Zhu and Kong (2023) who examine the effects of corruption on privatizations of state-owned enterprises in China. These authors exploit a natural experiment setup that particularly allows them to analyze the impact of anti-corruption campaigns in China on privatization. The authors use a difference-in-difference methodology and privatization is modeled as a binary Probit model in which the dependent variable takes on the value 1 if more than 5% of the shares of a state-owned enterprise are transferred to individuals or private entities during a given year and 0 otherwise. This variable is based on data on all privatizations of Chinese state-owned enterprises after 2007. The analysis allows them "… to document that state-owned enterprises significantly deepen privatization after the crackdown on corruption." As far as our main objective is concerned, we are particularly interested in Zhu and Kong's (2023) result that the reduction of corruption leads to an increase in privatization, thus confirming the idea that with a reduction in the opportunity to extract rents, decision-makers tend to privatize more as predicted by Laffont and Meleu's (1999) theory for high initial levels of corruption.

3. Data, variables, and descriptive statistics

Our paper seeks to estimate the relationship between privatization and corruption and test the prediction of Laffont and Meleu's (1999) theory in the case of the telecommunications sector. Our database consists in a pooled cross-sectional-time-series data on 103 countries for the

1985-2022 period.[8] In our analysis, we give particular attention to addressing the endogeneity of corruption. Let us discuss in turn the nature of the variables on which we collected data.

Privatization is captured by a binary variable taking the value 1 if the main fixed-line operator (the incumbent) is not 100% state-owned, and 0 if it is 100% state-owned. The source of data for this variable that was also used in Gasmi and Recuero Virto (2010) is the International Telecommunication Union (ITU). Concerning corruption in the public sector, we use the Bayesian Corruption Index, noted BCI hereafter.

BCI is a composite index of the perceived overall level of corruption, where corruption is defined as the abuse of public power for private gain. Given the hidden nature of corruption, direct measures are hard to come by, or inherently flawed, e.g., the number of corruption convictions. Instead, the opinions of inhabitants of a country on the level of corruption, management of companies operating in the country, non-governmental organizations, and officials working both in governmental and supra-governmental organizations are amalgamated. BCI takes values between 0 and 100, with an increase in the index corresponding to a rise in the level of corruption. This indicator is available from 1985 to 2017 and has been used by Peña Miguel and Cuadrado-Ballesteros (2019).

As for the control variables, considering that official financial aid often comes with conditionality, we use as a control variable the net official development assistance and official aid received in constant 2020 United States Dollars (USD), available from the World Bank's World Development Indicators (WDI) database. The presumption is that international financial institutions such as IMF and other official lenders require good governance and political stability, which must be put in place by both macroeconomic and structural reforms such as privatization to ensure the solvency of the country. We also expect privatization to be impacted by the cost of public funds which we proxy with a country's debt service expressed as a percentage of exports of goods, services, and primary income provided by the World Bank's WDI database.

Also, as in Gasmi and Recuero Virto (2010), we expect the privatization decision to be linked to the demand for fixed-line service. We thus incorporate the number of fixed-telephone subscriptions per 100 inhabitants. This variable refers to the sum of all active analogue fixed-telephone lines, voice-over-IP (VoIP) subscriptions, fixed wireless local loop (WLL) subscriptions, ISDN voice-channel equivalents, fixed public payphones, and satellite-based subscriptions provided to fixed locations that allow for a voice

[8] The list of these countries is presented in Table A4 in the appendix.

communication. We also control for population growth and economic development as proxied by real GDP per capita. An increase in population results in a higher need for fundamental services, including water, electricity, and healthcare, alongside infrastructure such as telecommunications services. Governments experiencing swift population growth may find it challenging to fulfill these needs because of financial limitations, scarce resources, or inefficiencies in managing public services. In such scenarios, turning to privatization can offer a way forward by drawing in private sector investments to enhance and enlarge telecommunications services, capitalizing on the private sector's efficiency, know-how, and resources. Countries possessing a higher real GDP per capita generally boast more developed and stable economic frameworks, making them more appealing destinations for investments, including increased private participations within the telecommunications industry.

All the control variables are lagged by one year to avoid possible endogeneity due to reverse causality. Table 1 gives the names of the variables, their contents, and the data sources from which we obtained them.

[Table 1 about here]

Table A1 in the appendix gives some descriptive statistics of these variables. This table reveals that approximately half of the observations are subject to privatization. The values of BCI range from 7.02 to 74.10. The average level of BCI is 45.96 on a scale of 0 (lowest level of corruption) to 100 (highest level of corruption), which is relatively high. The number of fixed line subscriptions per 100 inhabitants ranges from a minimum value of 0 to a value of around 120.49. The sample (overall) average value of this measure of fixed line penetration is about 16.87 subscriptions per 100 inhabitants.

The observations of yearly population growth take values ranging from -13.06% to 18.13%. These extreme values, however, are probably affected by contingent factors and are not very indicative of the general trend. The lowest value is achieved by Liberia in 1991 during the first civil War. The average value of population growth, which is more indicative of its trend, is 1.63%. The proxy variable for cost of public funds varies from a minimum close to 0 to a maximum value of 156.86% corresponding to Nicaragua in 1991. The overall average is 18.88%.

The observations on GDP per capita take values between 436.38 USD and 120,647.82 USD, with the lowest observation corresponding to Mozambique in 1992. The average value of the GDP per capita observations is 18,942.81 USD. The variable that measures net official development assistance and official aid received takes values between a minimum of -950 million USD corresponding to Thailand in 2003, and a maximum value slightly above 12 billion USD for Nigeria during the year 2006. The overall average value of this assistance variable is 643 million USD.

Table A2 in the appendix reports the variance inflation factors (VIFs). We see that all the VIFs are lower than 10, with an average VIF of 2.17. This suggests that there are no collinearity issues in our analysis.

4. Econometric analysis

4.1 IV Probit estimation results

Recall that our main objective is to test the theoretical prediction of Laffont and Meleu (1999) that corruption affect privatization in a nonlinear fashion, more specifically, that for low levels of corruption, privatization is increasing and for high levels it is decreasing. An inverse-U form of a relationship in which privatization is the dependent variable and corruption is an independent variable would then be consistent with this prediction. However, as discussed in section 2, theory also predicts that privatization may affect corruption. Hence, we need to take into account the endogeneity of corruption when estimating the privatization-corruption relationship.

Given that our dependent variable, privatization, is a binary outcome, it is appropriate to analyze the effects of corruption by estimating a Probit model with endogenous variables (IV Probit, hereafter). Both corruption and its square are considered endogenous. Let $privatization^*$ be the latent variable associated with the dichotomous observable variable $privatization$. The IV Probit model writes as follows:

$$\begin{aligned} privatization^*_{\mathrm{it}} &= \mathrm{c}'_{\mathrm{it}}\beta + \mathrm{x}'_{\mathrm{it}}\gamma + \varepsilon_{\mathrm{it}} \\ \mathrm{c}_{\mathrm{it}} &= \mathrm{x}'_{\mathrm{it}}\Pi_1 + \mathrm{z}'_{\mathrm{it}}\Pi_2 + \nu_{\mathrm{it}} \end{aligned} \tag{1}$$

where $\mathrm{c}_{\mathrm{it}} = (corrup_{\mathrm{it}}, corrup^2_{\mathrm{it}})$ is the two-dimensional vector of endogenous variables, $i = 1, \dots, N$ and $t = 1, \dots, T$ are indices that indicate respectively country and year, x_{it} is a k_1-dimensional vector of control variables assumed exogenous, Π_1 is its associated matrix of reduced-form parameters, z_{it} is a k_2-dimensionl vector of instrumental variables (IVs), Π_2 is its associated matrix of reduced-form parameters, β and γ are vectors of unknown structural parameters associated with respectively the endogenous variables (the components of c) and the exogenous variables (the components of x), and $\varepsilon_{\mathrm{it}}$ and ν_{it} are errors terms assumed to be centered and jointly normally distributed with variance-covariance matrix Σ. For the structural parameters to be identified we set $k_2 \geq 2$. The privatization variable is described as follows:

$$privatization_{\mathrm{it}} = \begin{cases} 1 & \text{if } \ privatization^{*}_{\mathrm{it}} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

To estimate this model, we perform the maximum likelihood estimation (MLE) procedure, which is known to be an efficient alternative to two-step estimation.[9] Standard errors are clustered at the country level to obtain valid inferences. The endogeneity of corruption is tested using a Wald test, which, as will be seen latter, rejects the null hypothesis of exogeneity of corruption.

To address the endogeneity of corruprion, we use government effectiveness, political stability, regulatory quality, and rule of law as IVs.[10] Governments that function effectively are more prone to enforce robust measures against corruption, thus directly affecting its prevalence. Political stability diminishes the likelihood of corruption by promoting consistent governance and policy execution. The presence of high-quality regulatory frameworks typically signifies the existence of clear and effective regulation, which serve to mitigate corruption by minimizing chances for wrongdoing. Furthermore, a well-established rule of law curtails corruption through stringent enforcement against power misuse and by upholding legal structures that prevent corrupt practices. Corruption in turn has an influence on privatization.

Note that government effectiveness, political stability, regulatory quality, and rule of law are closely tied to the governance context in which corruption arises, rather than directly to privatization actions. Their impact on (the outcomes of) privatization should primarily operate through their influence on the extent of corruption. In summary, government effectiveness, political stability, regulatory quality, and rule of law have a direct effect on corruption, and the latter in turn influences privatization.

Table 2 presents the results of the estimation of the IV Probit model. We see from this table that the Wald test rejects the null hypothesis of exogeneity of corruption. We also see that

[9] For theoretical details on the two-step estimation, see Newey (1987).
[10] As will be seen latter, the test of overidentifying restrictions shows that the null hypothesis of validity of these IVs is not rejected. In addition, the null hypothesis that these IVs are weak is rejected, as expected.

corruption has an inverted U-shaped impact on privatization. This indicates that as the level of of corruption control improves, the probability to privatize increases, but then there is a maximum threshold of control beyong which negative effects prevail, meaning that corruption reduces privatization. This confirms the positive theory of privatization of Laffont and Meleu (1999) for the case of telecommunications. Hence, a high level of corruption is bad news for privatization. The maximum threshold is around 51.36, on a scale of 0 (lowest level of corruption) to 100 (highest level of corruption). This means that for the level of corruption to hamper privatization, it only needs to be at about half of the maximum achievable level of corruption, which is significant.

[Table 2 about here]

The reasons behind this nonlinear effect largely echo the insights provided by Laffont and Meleu (1999) and Laffont (2005). Essentially, when corruption is minimal (less than 51.36 on a scale of 0 to 100), privatization presents opportunities for politicians and decision-makers to achieve personal profits, motivating them to privatize public enterprises. However, at sufficiently high levels of corruption (more than 51.36 on this scale), the potential for personal gains does not outweigh the benefits of control and additional advantages that politicians can derive from maintaining firms under state ownership. This decreases the probability to privatize.

Regarding the control variables, Table 2 reveals that fixed line penetration negatively influences privatization. Indeed, high levels of fixed line penetration imply a sufficiently developed market with little room for growth for newcomers, diminishing the sector's appeal to private investors who are in pursuit of significant growth prospects and thereby making privatization less enticing. An additional rationale for this finding pertains to the commitment to public service. In fact, high penetration rates signal an extensive public service provision. Consequently, governments may hesitate to privatize telecommunications services deemed vital for societal and economic integration, concerned that privatization might compromise service quality or escalate costs for users.

Results show that economic development increases the likelihood of privatization, that is, the higher the level of economic development, the higher the probability of privatizing public firms. This trend is often linked to economic development being paralleled by a move toward free-market policies, which encompass both deregulation and the privatization of public sectors. Governments in advancing economies might view privatization as a strategy to draw in foreign investment, enhance the efficiency of various sectors, and facilitate integration into the global economy. Additionally, economic advancement tends to be associated with the development of more robust regulatory frameworks. These frameworks are capable of effectively overseeing competition and safeguarding consumers within markets that have been privatized, making the process of privatization not only more feasible but also more appealing.

Table 3 presents the findings from the Anderson and Rubin (1950) test of overidentifying restrictions (OIDR), assessing the validity of the IVs used. It also reports the Cragg and Donald (1993) minimum eigenvalue statistic (CDME) and the maximum critical value from Stock and Yogo (2005), associated with the Limited Information Maximum Likelihood (LIML) size of a nominal 5% Wald test. These metrics, the CDME and the maximum critical value, are utilized to conduct the Stock and Yogo (2005) test, which assesses the strength of the IVs. We see from Table 3 that the test does not reject the null hypothesis concerning their validity. Hence, the IVs are valid. Furthermore, the potency of these IVs is demonstrated as the CDME statistic exceeds the maximum critical value, leading to the rejection of the null hypothesis that the IVs are weak.

[Table 3 about here]

4.2 Robustness checks

To assess the robustness of the inverted-U shaped relationship between corruption and privatization, we employ impact evaluation methods to demonstrate that corruption positively influences privatization when the level of corruption is below the threshold of 51.36 on a scale of 0 to 100, and has a negative impact when the level of corruption exceeds this threshold. We utilize two different and widely used impact evaluation methods, namely, entropy balancing and (pure) propensity score matching, along with four alternative matching methods, namely, kernel matching, local linear regression (LLR) matching, one-to-one matching, and radius matching. The primary quantity of interest in employing these methods is the average treatment effect on the treated (ATT), which reflects the impact of corruption on the likelihood of privatization. Note that impact evaluation methods are also a way of handling the endogeneity of corruption when analyzing its effects on privatization.

More precisely, to analyze the effect of corruption on privatization when the level of corruption is below the threshold of 51.36, we create a dummy variable equal to 1 if $corrup \leq 51.36$ and 0 otherwise (that is, $corrup > 51.36$). In this case, the "treatment" group is composed of observations (the "treated" units) for which $corrup \leq 51.36$ while the "control" group comprises those observations (the "control" units) for which $corrup > 51.36$.

Similarly, to analyze the effect of corruption on privatization when the level of corruption exceeds the threshold of 51.36, we create a dummy variable equal to 1 if $corrup > 51.36$ and 0 otherwise (that is, $corrup \leq 51.36$). In this case, the "treatment" group is composed of observations (the "treated" units) for which $corrup > 51.36$ while the "control" group comprises those observations (the "control" units) for which $corrup \leq 51.36$.

As will be show latter, all these estimations show that corruption increases the probability of privatization when its level is below 51.36, but decreases this probability when its level is above 51.36. This underscores the robustness of our findings.

4.2.1 Entropy balancing

The entropy balancing method is an innovative and effective impact evaualtion method introduced by Hainmueller (2012). It operates by adjusting a dataset through weights to ensure the distributions of covariates meet certain moment conditions, thereby facilitating the analysis of treatment effects by handling the endogeneity of the independent or treatment variable. One of the significant strengths of entropy balancing is its ability to achieve high covariate balance without sacrificing data integrity, as it adjusts the weights to stay as close as possible to their base values. This approach minimizes reliance on models and incorporates adjustments for panel data structures through the inclusion of year and individual dummies. Through Monte Carlo simulations and empirical application, Hainmueller (2012) demonstrates that entropy balancing outperforms traditional impact evaluation methods such as propensity score matching, mahalanobis matching, and genetic matching, in terms of both root mean squared error and estimation bias.

The process of applying entropy balancing to evaluate the impact of corruption on privatization unfolds in two steps. The first step involves the computation of weights for the control group by enforcing balancing constraints on the sample moments of observable characteristics, generally aiming for parity in the average covariates between treated and control groups. This ensures comparability by making the characteristics of the control group closely mirror those of the treated group. Following this, the method integrates these entropy balancing weights into a regression analysis, with privatization as the outcome variable and corruption dummy as the independent variable, yielding the ATT. This second step typically employs a Probit model due to the binary nature of the outcome variable.

The efficacy of the entropy balancing method is validated through a comparative analysis of covariate means between treated and control groups, both pre and post-weight application, as detailed in the appendix's Table A3. The table reveals that, prior to weighting, there were discrepancies in covariate means between groups, which are neutralized post-application, achieving zero difference and thus confirming the balancing property is achieved.

Table 4 reports the results of the estimation of the ATT using the entropy balancing method. The analysis delineates the impact of excluding or including matching covariates and fixed effects in the second step of entropy balancing. Specifically, columns (1) through (4) detail outcomes when the matching covariates are not factored in. Column (1) omits both year and country fixed effects, showcasing results without adjustments for temporal and geographic specificities. Conversely, Columns (2) and (3) incorporate either year or country fixed effects, respectively, acknowledging their role in adjusting for macroeconomic fluctuations and country-specific influences on privatization and corruption. Column (4) includes both year and country fixed effects, providing a more comprehensive control for both sets of variables simultaneously. Columns (5) through (8) replicate this framework but with an inclusion of the matching covariates used in the first step of the entropy balancing methodology. This inclusion is pivotal for refining the efficiency of estimations by accounting for covariates that align the treated and control groups more closely.

[Table 4 about here]

The upper part of Table 4 reports the results where the treatment is $corrup \leq 51.36$ whereas the bottom part presents the results for $corrup > 51.36$ as the treatment. We see from this table that irrerspecctive of the specification, corruption positively influences privatization when the level of corruption is below the threshold of 51.36 and has a negative impact when the level of corruption exceeds this threshold. This confirms our previous findings. In each case, the relative stability of the estimated ATT over the eight specifications shows the consistence of our the resulsts.

4.2.2 Propensity score matching

At the heart of the propensity score matching (PSM) technique lies the goal of transforming observational data into a format akin to a quasi-experimental study, thereby allowing for an analysis of the impact of a specific treatment on outcomes. PSM hinges on the concept of comparing counterfactual outcomes. A missing potential outcome for each observation is calculated by averaging the outcomes of similar observations under the alternate treatment level. The basis for determining similarity is the calculation of "propensity scores," or the likelihood of receiving the treatment, grounded in observable characteristics. These scores facilitate meaningful comparisons between treatment and control groups (Rosenbaum and Rubin, 1983).

In this study, the propensity score is defined by the probability of experiencing a level of corruption either below or equal to 51.36 for the analysis of the initial phase of the inverted U-shaped curve, or above 51.36 for the latter phase, based on matching covariates. A Probit model is utilized to generate these propensity scores. Upon the calculation of propensity scores, we proceed to match treated and control units based these scores to ascertain the ATT. To ensure the validity of our matching process, we conduct balancing tests.

Table 5 reports the ATT obtained from the PSM. For the sake brevity, we do not report the results of the Probit models allowing to obtain propensity. These results are available upon request. The ATT is positive and significant when $corrup \leq 51.36$, and negative and significant when $corrup > 51.36$. This confirms our main result, that is, corruption increases the probability to privatize when its level is below the threshold of 51.36, but reduces this probability when the level of corruption exceeds this threshold.

[Table 5 about here]

Table 5 also reports the results from the Rubin's B and R tests to assess whether the balancing property is achieved (Rubin, 2001). We see from this table that, in all cases ($corrup > 51.36$ or $corrup \leq 51.36$), Rubin's R statistic lies within the $[0.5; 2]$ interval, and the Rubin's B statistic is lower than 25%. This indicates that the balancing property is achieved (Rubin, 2001).

4.2.3 Alternative matching approaches

In our final analysis, we estimate the ATT employing four distinct matching methodologies that are prevalent alternatives to the traditional PSM approach, each with unique characteristics and applications. These methods include kernel matching, LLR matching, one-to-one matching, and radius matching, diverging from pure PSM in several ways.

Kernel and LLR matching represent semi-(non)parametric strategies, utilizing weighted averages from a comprehensive set of control observations to construct counterfactual outcomes. The primary benefit of these approaches is the reduction in variance and, consequently, enhanced precision in estimates due to the broader use of data. LLR matching extends beyond kernel matching by incorporating a linear component in a treated unit's propensity score, offering advantages in scenarios where the propensity score distribution exhibits gaps or when there is an asymmetrical distribution of comparison observations around the treated observation (Caliendo and Kopeinig, 2008).

One-to-one matching involves matching treated units with the nearest neighbor within the control group based on propensity scores. While this method may face efficiency challenges, it ensures minimal propensity score disparity between matched pairs. It reduces bias but potentially at the expense of precision. Huber et al. (2013) advocate for the robustness of the one-to-one matching, especially under misspecifications in the propensity score model, noting its consistency when the misspecified model is a monotone transformation of the actual model.

Radius matching, a form of caliper matching, sets a threshold or "caliper" for the acceptable difference in propensity scores, matching a treated unit with all control units falling within this predefined caliper. This approach can be seen as a one-to-many caliper matching strategy, and is designed to balance the trade-off between bias reduction and the inclusion of a sufficient number of comparison observations.

Table 6 presents the results of the estimation of the ATTs using the different methods. The upper part of this table reports results where the treatment is $corrup \leq 51.36$, whereas the bottom part presents the results for $corrup > 51.36$ as the treatment.

[Table 6 about here]

Table 6 indicates that, regardless of the matching approach used, the probability of privatization increases when the level of corruption does not exceed the threshold of 51.36, but decreases once it does. The statistics from Rubin's R and B tests meet the required standards. Specifically, the Rubin's R statistic falls within the $[0.5; 2]$ interval, and the Rubin's B statistic is less than 25%, indicating that the balancing property has been achieved (Rubin, 2001). These results support the robustness of our previous findings.

5. Conclusion

Using a dataset on 103 countries' telecommunications sector covering the 1985-2022 period, this paper provides evidence of a nonlinear relationship between privatization and corruption in which the latter has a quadratic effect on the former of an inversely U-shaped form. This finding is in line with the positive theory of privatization developed by Laffont and Meleu (1999) and contradicts numerous other theoretical papers, which argue for a linear relationship.

Using the Bayesian Corruption Index to measure the level of corruption, we obtain exactly the inverse U-shaped relationship as predicted by the Laffont and Meleu's (1999) model, in the case of the telecommunications sector. This relationship suggests that at low levels of corruption, an increase in corruption could potentially facilitate privatization processes, but beyond a certain point, further increases in corruption would hinder privatization. The results show that the threshold value of corruption, beyond which the level of corruption reduces the probability of privatization, is about 51.36 on a scale of 0 (lowest level of corruption) to 100 (highest level of corruption).

Ultimately, the nonlinear effect highlights the complexity of the relationship between corruption and privatization. This complexity necessitates sophisticated and comprehensive policy strategies that specifically address corruption within each (unique) context. Broadly speaking, effectively tackling corruption can significantly improve the outcomes of privatization. This is particularly true in enhancing the efficiency, competitiveness, and quality of telecommunications services. To address corruption, the establishment of robust and efficient public policies is essential. These policies could be envisioned to follow five primary directions.

First, acknowledging the intricate connection between corruption and privatization necessitates that anti-corruption efforts be carefully tailored and focused. This may include concentrating on particular phases of the privatization journey that are exceptionally prone to corruption, or dealing with certain types of corruption that have a detrimental impact on privatization efforts. Second, to effectively combat corruption, it is crucial to boost transparency and accountability across both public and private spheres. Implementing policies that enhance the openness of the privatization process, such as conducting transparent bidding and establishing explicit selection criteria, can reduce corruption's adverse effects.

Third, and relatedly, involving civil society and the general public in the privatization initiative offers an extra safeguard and ensures greater accountability. Initiatives such as public engagement, transparency measures, and corruption reporting mechanisms should enable citizens to actively contribute to the integrity of the privatization process. Fourth, it is crucial to reinforce legal and institutional structures to fight corruption more efficiently. This might include overhauling public sector bodies, refining legal regulations to penalize corruption more effectively, and promoting an ethic of honesty within the telecommunications industry. Fifth, adjusting economic policies to tackle the fundamental causes of corruption and foster a conducive environment for wholesome privatization is necessary. This could mean implementing reforms that improve the business climate, decrease bureaucratic hurdles, and boost competition in the telecommunications sector.

The present research could be extended in at least four directions. First, it is important to determine whether the nonlinear effects of corruption on privatization are specific to the telecommunications sector or if they should be extended to other infrastructure sectors. Future studies could conduct a comparative analysis of the effects of corruption in the telecommunications sector and other infrastructure sectors such as water, transport, energy, etc. Assuming an inverted U-shaped relationship is also found in other infrastructure sectors, analyzing the differences in the threshold value of corruption, beyond which the level of corruption diminishes privatization, could lead to important conclusions regarding the variations in the extent of effort that should be made by public authorities to curb the adverse effects of corruption in each sector.

Second, in this paper, we measure privatization in the telecommunications sector through a binary variable due to a lack of data. Future research should attempt to construct a multicategorial variable that captures varying degrees of privatization. This would allow for a finer-grained analysis of the privatization process. Third, analyzing the roles of poverty, unemployment, the informal economy, and political instability in the corruption-privatization nexus is potentially a promising avenue for future research. These factors may actually exacerbate corruption, thereby leading to differentiated degrees of privatization according to their levels. Fourth, since our findings indicate that the level of corruption decreases privatization only when it reaches a certain point, future studies could analyze the effects of corruption on the costs and benefits of privatization in the telecommunications sector.

Appendix

[Table A1 about here]

[Table A2 about here]

[Table A3 about here]

[Table A4 about here]

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The privatization-corruption relationship is nonlinear: Evidence from 1985-2022 data on telecommunications in 103 countries

Tables

Table 1. Variables and data sources+

Variable name	Variable content	Source
Dependent variable		
$privatization$	Privatization. Binary variable taking the value 1 if the main fixed-line operator (the incumbent) is not 100% state-owned, and 0 if it is 100% state-owned.	ITU
Independent variable		
$corrup$	Corruption measured by the Bayesian Corruption Index. Ranges from 0 (lowest level of corruption) to 100 (highest level of corruption).	UG
Control variables		
$costpublicf$	Total debt service (% of exports of goods, services, and primary income) (in log).	WDI
$popgrowth$	Annual population growth rate.	WDI
$gdppc$	Economic development, measured by real GDP per capita (in log).	WDI
$fixedline$	Fixed line penetration, measured by the number of fixed-telephone subscriptions per 100 inhabitants (in log).	ITU
$aiddev$	Net official development assistance and official aid received, expressed in constant 2020 USD. Rescaled to the $[0; 1]$ interval using the "min-max" method. This adjustment accounts for negative values, which can be significantly high in absolute values.	WDI

+ ITU: International Telecommunication Union; UG: University of Gent; WDI: World Bank's World Development Indicators database; log: natural logarithm.

Table 2. MLE parameter estimates of the IV Probit+

$corrup$	0.719***
	(0.206)
$corrup^2$	-0.007***
	(0.002)
Lagged $fixedline$	-0.374***
	(0.126)
Lagged $popgrowth$	-0.111
	(0.109)
Lagged $costpublicf$	0.115
	(0.139)
Lagged $gdppc$	0.436**
	(0.218)
Lagged $aiddev$	-4.479
	(3.840)
Constant	-19.439***

	(5.053)
Wald test of overall significance	355.89***
Wald test of exogeneity	18.90***
Observations	752

+ Robust standard errors, clustered at the country level, are presented in parentheses. *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Table 3. Tests of validity and weakness of instruments+

H_0		Statistic
Instruments are valid	OIDR	3.45
	p-value	0.18
Instruments are weak	CDME	4.84
	Critical value	4.72

+ OIDR: Overidentifying restrictions test statistic (Anderson and Rubin, 1950); CDME: Cragg and Donald (1993) minimum eigenvalue statistic; Critical value is the highest critical value relating to the LIML size of nominal 5% Wald test (Stock and Yogo, 2005).

Table 4. Robustness checks: Entropy balancing treatment effect estimation+

	(A) Treatment: $corrup \leq 51.36$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATT	0.158***	0.188***	0.216*	0.154***	0.155***	0.185***	0.234**	0.159***
	(0.030)	(0.028)	(0.120)	(0.026)	(0.029)	(0.029)	(0.115)	(0.022)
Covariates in the second step	No	No	No	No	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	1,446	1,446	918	918	1,446	1,446	918	918
	(B) Treatment: $corrup > 51.36$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATT	-0.163***	-0.197***	-0.285**	-0.173**	-0.157***	-0.186***	-0.218**	-0.167**
	(0.034)	(0.028)	(0.111)	(0.075)	(0.038)	(0.029)	(0.092)	(0.077)
Covariates in the second step	No	No	No	No	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	1446	1446	918	918	1446	1446	918	918

+ ATT: Average treatment effect on the treated. Standard errors in parentheses .

Table 5. Robustness checks: Propensity score matching treatment effect estimation+

	(A) Treatment: $corrup \leq 51.36$	(B) Treatment: $corrup > 51.36$
ATT	0.134***	-0.153***
	(0.033)	(0.037)
Rubin's B statistic	15.1%	20.8%
Rubin's R statistic	1.31	1.09
Observations	1,446	1,446

+ ATT: Average treatment effect on the treated. Abadie-Imbens robust standard errors are shown within parentheses. 10 matches per observation specified. Employing a higher count of matches does not alter the outcome. *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Table 6. Robustness checks: Treatment effect estimation using alternative matching approaches[+]

	(A) Treatment: $corrup \leq 51.36$			
	Kernel matching	LLR matching	One-to-one matching	Radius matching
ATT	0.148***	0.157***	0.165***	0.147***
	(0.031)	(0.032)	(0.045)	(0.029)
Rubin's B statistic	16.6%	13.9%	10.9%	15.6%
Rubin's R statistic	1.13	1.06	1.03	1.12
Observations	1,446	1,446	1,446	1,446
	(B) Treatment: $corrup > 51.36$			
	Kernel matching	LLR matching	One-to-one matching	Radius matching
ATT	-0.170***	-0.152***	-0.157***	-0.168***
	(0.035)	(0.036)	(0.046)	(0.038)
Rubin's B statistic	20%	22%	22.7%	19.5%
Rubin's R statistic	1.39	0.96	1.29	1.33
Observations	1,446	1,446	1,446	1,446

[+] ATT: Average treatment effect on the treated. LLR: Local linear regression. Standard errors are in parentheses. For One-to-one matching and Radius matching, Abadie-Imbens robust standard errors are reported. *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Table A1. Summary statistics[+]

Variable	Observation	Mean	St. Dev.	Min.	Max.
$privatization$	4003	0.49	0.50	0	1
$corrup$	3160	45.96	16.69	7.02	74.10
$fixedline$	3690	1.70	1.88	-5.10	4.79
	3697	[16.87]	[19.32]	[0.00]	[120.49]
$popgrowth$	3861	1.63	1.47	-13.06	18.13
$costpublicf$	2212	2.57	0.99	-5.63	5.06
	2212	[18.88]	[15.73]	[0.00]	[156.86]
$gdppc$	3338	9.19	1.26	6.08	11.70
	3338	[18942.81]	[20436.88]	[436.38]	[120647.82]
$aiddev$	2848	0.06	0.03	0.00	0.48
	2848	[6.43e+08]	[9.12e+08]	[-9.50e+08]	[1.22e+10]

[+] Actual values (that is, without transformation) are in brackets.

Table A2. Variance inflation factors (VIFs)

$corrup$	$fixedline$	$popgrowth$	$costpublicf$	$gdppc$	$aiddev$	Mean VIF
1.19	4.65	1.62	1.04	3.40	1.10	2.17

Table A3. Entropy balancing: Means of the covariates before and after weighting[+]

	Variable	Before weighting			After weighting		
		(1) Treated	(2) Control	(1)-(2)	(1) Treated	(2) Control	(1)-(2)
$corrup \leq 51.36$	Lagged $fixedline$	1.83	0.85	0.98	1.83	1.83	0
	Lagged $popgrowth$	1.45	1.85	-0.4	1.45	1.45	0
	Lagged $costpublicf$	2.22	2.36	-0.14	2.22	2.22	0
	Lagged $gdppc$	8.76	8.35	0.41	8.76	8.76	0
	Lagged $aiddev$	0.06	0.06	0	0.06	0.06	0
$corrup > 51.36$	Lagged $fixedline$	0.85	1.83	-0.98	0.85	0.85	0
	Lagged $popgrowth$	1.85	1.45	0.4	1.85	1.85	0

Lagged $costpublicf$	2.36	2.22	0.14	2.36	2.36	0
Lagged $gdppc$	8.35	8.76	-0.41	8.35	8.35	0
Lagged $aiddev$	0.06	0.06	0	0.06	0.06	0

[+] See Table 1 for the definition of the variables.

Table A4. List of the countries

Afghanistan; Albania; Algeria; Angola; Argentina; Armenia; Azerbaijan; Bangladesh; Belarus; Belize; Benin; Bhutan; Bolivia; Bosnia and Herzegovina; Botswana; Brazil; Burkina Faso; Burundi; Cambodia; Cameroon; Cape Verde; China; Colombia; Comoros; Congo, Dem. Rep.; Congo, Rep.; Costa Rica; Côte d'Ivoire; Dominica; Dominican Republic; Ecuador; Egypt, Arab Rep.; El Salvador; Eswatini; Ethiopia; Fiji; Gabon; Gambia, The; Georgia; Ghana; Grenada; Guatemala; Guinea; Guyana; Haiti; Honduras; India; Indonesia; Iran, Islamic Rep.; Jamaica; Jordan; Kazakhstan; Kenya; Kyrgyz Republic; Lao PDR; Lebanon; Lesotho; Liberia; Madagascar; Malawi; Maldives; Mali; Mauritania; Mauritius; Mexico; Moldova; Mongolia; Montenegro; Morocco; Mozambique; Myanmar; Nepal; Nicaragua; Niger; Nigeria; North Macedonia; Pakistan; Paraguay; Peru; Philippines; Rwanda; Samoa; Senegal; Serbia; Sierra Leone; Somalia; South Africa; Sri Lanka; St. Lucia; St. Vincent and the Grenadines; Sudan; Tanzania; Thailand; Timor-Leste; Togo; Tunisia; Türkiye; Uganda; Ukraine; Vanuatu; Vietnam; Zambia; Zimbabwe.