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Firm-Level and Public-Sector Corruption Perceptions: The Nexus

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Abstract

Understanding how firm-level corruption shapes national corruption perceptions is crucial for both policymakers and businesses, as it provides evidence to strengthen governance frameworks and foster integrity-driven corporate environments. This study investigates the relationship between firm-level corruption experiences and the Corruption Perceptions Index (CPI), a widely used measure of perceived public-sector corruption. Three indicators from the World Bank Enterprise Surveys are used to capture firm-level corruption: firms' bribery incidence, gifts to tax officials, and informal payments to public officials. The analysis covers data from 36 countries and employs a rigorous methodological approach, including mean-based estimation techniques such as Gaussian Generalized Linear Models (Gaussian GLM) and Robust Least Squares (RLS), as well as Bootstrap Quantile Regression (BQR). The Gaussian GLM and RLS results indicate that all three indicators have a significant negative impact on the CPI, meaning that more frequent occurrences of these firm-level corrupt practices are associated with lower CPI scores, which reflect higher perceived levels of corruption. The BQR analysis further reveals that the negative impact of two firm-level corruption indicators, bribery incidence and gifts to tax officials, is concentrated in the lower quantiles, indicating a stronger effect in countries with low CPI scores or higher apparent corruption. These findings underscore the importance of strengthening institutional oversight and promoting business integrity at the firm level, as reducing routine corruption in business interactions can meaningfully enhance a country's overall corruption perception and institutional credibility.



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1. Introduction

Corruption remains a persistent challenge across the globe, undermining democratic governance, economic development, and public trust [1–3]. One of the most influential tools for capturing the perceived extent of corruption is the Corruption Perceptions Index (CPI) [4]. The CPI aggregates assessments from experts and business executives to provide a comparative measure of

public-sector corruption in countries worldwide. With scores ranging from 0 (highly corrupt) to 100 (very clean), the CPI is widely used by governments, investors, international organizations, and civil society as a benchmark for institutional integrity [5, 6]. However, despite its widespread use, the CPI reflects perceptions rather than objective corruption levels, making it susceptible to influences from both formal institutional

factors and the everyday experiences of those who interact with public institutions.

In this context, the role of firm-level corruption becomes increasingly relevant. Many businesses, especially in developing economies, frequently encounter demands for bribes, are expected to provide unofficial “gifts” to tax officials, or engage in informal payments to secure licenses or services [7, 8]. These practices, while often normalized within local business environments, represent critical micro-level interactions that may contribute to broader perceptions of systemic corruption [9, 10]. When these experiences are widespread, they can shape how both domestic and international observers evaluate a country’s governance landscape [11, 12]. Therefore, while firm-level corruption is frequently studied in relation to firm performance, access to finance, or regulatory burdens, its potential role in influencing national-level corruption perceptions (as captured by the CPI) has not been fully explored. This creates a blind spot in both academic and policy-oriented research on corruption, particularly given that the CPI is often used as a proxy for overall institutional quality.

For instance, in Mexico, numerous firms in the construction and procurement sectors have been implicated in schemes involving bribes paid to local officials to win public contracts, practices that became particularly visible during national anti-corruption drives and were widely reported in the press [13, 14]. In African countries, enterprise surveys have highlighted that many firms routinely make informal payments to customs officials to expedite the clearance of goods, a practice that has become an accepted part of doing business but also signals institutional weakness [15]. Similarly, in Bulgaria and Romania, private firms have reported expectations to provide unofficial “gifts” during tax inspections, reflecting enduring bureaucratic opacity despite EU membership [16]. Meanwhile, in Cambodia, companies in the garment and manufacturing sectors often face demands for facilitation payments from licensing authorities, contributing to the country’s persistently low CPI scores [17, 18]. Though these transactions may appear isolated or routine at the firm level, their cumulative effect across industries and regions reinforces a national image of entrenched corruption, shaping how both domestic stakeholders and international observers assess governance quality.

Theoretically, this study draws from institutional and signaling frameworks. Institutional theory emphasizes that the prevalence of corruption reflects the strength of formal rules and the embeddedness of informal norms within a given society [19–21]. Weak enforcement mechanisms and lack of accountability create fertile

ground for corruption to flourish [22, 23]. In parallel, signaling theory offers a compelling lens to interpret how observed behaviors, such as frequent bribery or informal transactions, may serve as credible signals to external evaluators about the institutional environment [24]. From this perspective, high levels of firm-level corruption may indicate to observers that corruption is not isolated or incidental, but rather systemic [25, 26]. Thus, micro-level interactions are not merely private affairs, they contribute to shaping broader perceptions and reputations at the national level.

Empirically, most studies on the determinants of public perception of corruption have focused on macro-level variables. These include Gross Domestic Product (GDP), as examined by d’Agostino et al. [27], Gründler & Potrafke [28], Hardi et al. [29], Moiseev et al. [30], and Scholl & Schermuly [31]; political stability, as studied by Beju et al. [32], Farzanegan & Witthuhn [33], and Schumacher [34]; economic and social freedom, as addressed by Ambrey et al. [35], Hardi et al. [36], and Pieroni & D’Agostino [37]; and judicial independence, as explored by Buscaglia [38], Ferreyra [39], and Wang & Liu [40]. These factors are undoubtedly important, but they offer an incomplete picture. A growing body of research using the World Bank Enterprise Surveys, by the likes of Amin & Soh [41], Khan et al. [42], Krichi et al. [43], Mohammed & Bunyaminu [44], and Williams & Kedir [45], has revealed that corruption at the firm level remains pervasive and varies significantly across countries. However, few studies have empirically examined how these firm-level experiences relate to variations in public perceptions of corruption, as captured by CPI scores. Those that do tend to rely on average effects, potentially masking differences across countries with varying baseline levels of corruption. As such, the link between micro-level corruption and national corruption perception remains underexamined, despite its theoretical plausibility and practical relevance.

This study addresses that gap by analyzing how three firm-level corruption indicators (bribery incidence, gift expectations to tax officials, and informal payments) affect a country’s CPI score. Using 2023 cross-sectional data from the World Bank Enterprise Surveys across 36 countries, it applies Gaussian GLM, Robust Least Squares, and Bootstrap Quantile Regression to capture both average effects and variations across different corruption contexts. The study is expected to reveal how routine business-level corruption shapes national perceptions, with potential implications for policymakers aiming to curb everyday graft and for businesses facing reputational risks. Ultimately, it may support efforts to strengthen governance through greater transparency in public-private interactions.

Table 1. Details of variables.

Status	Variable	Symbol	Unit Measurement	Source
Dependent	Corruption Perception Index	CPI	Scale 0-100	TI [4]
Main Independent	Bribery Incidence	BI	% of Total Firms	WBES [46]
	Gift Expectation	GE	% of Total Firms	WBES [46]
	Informal Payment	IP	% of Total Firms	WBES [46]
Control Independent	GDP per Capita	GDPC1	Constant LCU	WDI [47]
		GDPC2	Current US Dollar	WDI [47]
		GDPC3	Current LCU	WDI [47]

2. Materials and Methods

2.1. Data and Variables

The study uses cross-sectional data from the year 2023 for the firm-level corruption experience indicators, as this is the most recent year for which data are available. Accordingly, the dependent variable (CPI) and the control variable (GDP per capita) are also taken from 2023 to ensure data alignment. The CPI is sourced from Transparency International [4], the firm-level corruption indicators are obtained from World Bank Enterprise Surveys [46], and GDP per capita is drawn from the World Bank's World Development Indicators [47]. Detailed variable information can be seen in Table 1.

The study includes a total of 36 countries based on the availability of firm-level corruption indicator data: Bosnia and Herzegovina, Botswana, Bulgaria, Cambodia, Central African Republic, Chad, Colombia, Costa Rica, Cote d'Ivoire, Croatia, El Salvador, The Gambia, Ghana, Greece, Hungary, Indonesia, Kyrgyz Republic, Lesotho, Mauritius, Mexico, Montenegro, Morocco, Nepal, North Macedonia, Paraguay, Peru, Philippines, Portugal, Romania, Rwanda, Seychelles, Sierra Leone, Tanzania, Togo, Vanuatu, and Viet Nam.

2.2. Variable Definition and Conceptual Framework

2.2.1. Corruption Perception Index (CPI)

The Corruption Perceptions Index (CPI) is the dependent variable in this study and serves as a widely recognized measure of perceived public-sector corruption at the national level. Developed and published annually by Transparency International [4], the CPI aggregates expert assessments and opinion surveys to evaluate how corrupt a country's public sector is perceived to be. The index is scaled from 0 to 100, where a score of 0 indicates a highly corrupt public sector and a score of 100 indicates a very clean one. The CPI draws on multiple data sources from independent institutions, including assessments by business executives, risk analysts, and governance experts. Its methodological consistency, broad coverage, and international comparability make it a reliable proxy

for capturing the overall perception of corruption within a country.

2.2.2. Firm-Level Corruption Experience Indicators

This study employs three firm-level corruption experience indicators as the main independent variable sourced from the World Bank Enterprise Surveys [46]: (1) bribery incidence (BI), measured as the percentage of firms that reported experiencing at least one bribe payment request; (2) firms expected to give gifts in meetings with tax officials (GE), indicating the percentage of firms reporting such expectations during interactions with tax authorities; and (3) informal payments to public officials (IP), reflecting the percentage of firms that reported making unofficial payments to government officials. These indicators capture distinct yet interrelated aspects of corruption in business-state interactions. To assess their individual effects on the CPI, each indicator is examined in a separate regression model using a decomposition approach. This method allows for clearer identification of the unique contribution of each form of corruption to national-level perceived corruption, while avoiding multicollinearity and enhancing interpretability and methodological precision.

2.2.3. GDP per capita

To enhance methodological rigor and ensure robustness of results, the study incorporates three different GDP per capita measurement units, constant local currency unit (LCU), current LCU, and current US dollars, as control variables in separate regression models. This strategy allows for the assessment of whether the relationship between firm-level corruption experiences and the CPI holds consistently across varying economic valuation contexts. By isolating each GDP measure in distinct models, the analysis mitigates multicollinearity concerns. This decomposition also strengthens the reliability of the findings by testing the sensitivity of results to alternative representations of national income and market size levels. Together, these steps ensure that conclusions drawn are not driven by a particular income metric.

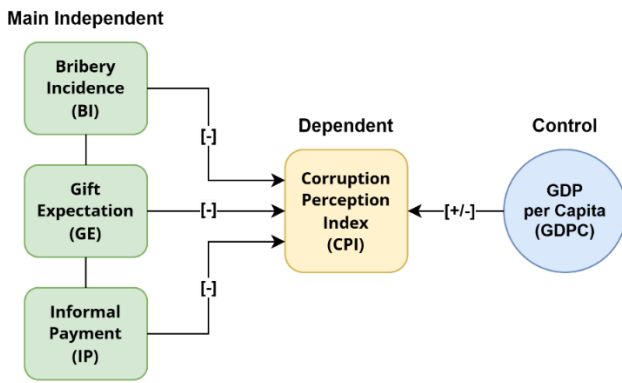


Figure 1. Conceptual framework of the study.

2.2.4. Conceptual Framework

As shown in Figure 1, this study conceptualizes that firm-level corruption experiences, specifically bribery incidence, gift expectations during tax meetings, and informal payments to public officials, contribute to shaping the overall perception of corruption within a country, as measured by the CPI. These firm-level practices reflect the frequency and normalization of informal and unethical interactions between businesses and public institutions, which may signal systemic governance weaknesses to both domestic observers and international stakeholders. The CPI, although a perception-based aggregate indicator, is influenced by such patterns of behavior. Accordingly, the study hypothesizes that firm-level corruption indicators have a negative impact on CPI, where higher levels of such practices are associated with lower CPI scores (i.e., higher perceived corruption).

GDP per capita, measured in different units, is included as a control variable to account for the role of economic development in shaping both corruption levels and their perception. The effect of GDP can be either positive or negative, depending on the context. By modeling each corruption indicator separately through a decomposition approach, the framework allows for identifying which types of firm-level corruption most strongly correlate with national corruption perceptions.

2.3. Model Specification

The empirical focus of this study is to examine the impact of three firm-level corruption experience indicators on the Corruption Perceptions Index (CPI), with three different GDP per capita measurement units included as control variables. The econometric analysis adopts a decomposition approach, assessing the impact of each main independent variable on the dependent variable (CPI) in separate models, using the three GDP per capita measurement units as controls. This approach allows the individual contributions of each main independent

variable to be more clearly identified and interpreted. Additionally, the use of multiple GDP per capita measurement units as control variables enhances the methodological rigor of each employed model. Equation 1 presents the mathematical specification of the study.

$$CPI = f(GDPC, FLCE) \tag{1}$$

Where CPI is the corruption perception index, GDPC is the three different GDP per capita measurement units, and FLCE is the three firm-level corruption experience indicators.

Subsequently, the decomposition of the econometric model based on Equation 1 is detailed in Equations 2 through 10.

$$CPI_i = \beta_{10} + \beta_{11}BI_i + \beta_{12} \begin{bmatrix} GDPC1_i \\ GDPC2_i \\ GDPC3_i \end{bmatrix} + \varepsilon_i \tag{2-4}$$

$$CPI_i = \beta_{20} + \beta_{21}GE_i + \beta_{22} \begin{bmatrix} GDPC1_i \\ GDPC2_i \\ GDPC3_i \end{bmatrix} + \varepsilon_i \tag{5-7}$$

$$CPI_i = \beta_{30} + \beta_{31}IP_i + \beta_{32} \begin{bmatrix} GDPC1_i \\ GDPC2_i \\ GDPC3_i \end{bmatrix} + \varepsilon_i \tag{8-10}$$

Here, *i* represents the country, β_{10} to β_{30} is the constant, β_{11} to β_{32} are the coefficients, and ε is the error term.

Since the dependent, control, and independent variables have different units of measurement, the data were transformed into their natural logarithmic form, allowing the results to be interpreted as percentage changes rather than absolute changes. The final econometric model of the study is shown in Equations 12-21.

$$\ln CPI_i = \beta_{10} + \beta_{11} \ln BI_i + \beta_{12} \begin{bmatrix} \ln GDPC1_i \\ \ln GDPC2_i \\ \ln GDPC3_i \end{bmatrix} + \varepsilon_i \tag{11-13}$$

$$\ln CPI_i = \beta_{20} + \beta_{21} \ln GE_i + \beta_{22} \begin{bmatrix} \ln GDPC1_i \\ \ln GDPC2_i \\ \ln GDPC3_i \end{bmatrix} + \varepsilon_i \tag{14-16}$$

$$\ln CPI_i = \beta_{30} + \beta_{31} \ln IP_i + \beta_{32} \begin{bmatrix} \ln GDPC1_i \\ \ln GDPC2_i \\ \ln GDPC3_i \end{bmatrix} + \varepsilon_i \tag{17-19}$$

2.4. Methods

2.4.1. Gaussian Generalized Linear Models (Gaussian GLM)

The Gaussian GLM is suitable for modeling a continuous dependent variable like the CPI and assumes normally distributed errors, making it well-suited for estimating linear relationships in this context. An important advantage of the Gaussian GLM is its flexibility in accommodating both continuous and categorical predictors, while maintaining interpretability of coefficients in terms of marginal effects [48, 49]. Firm

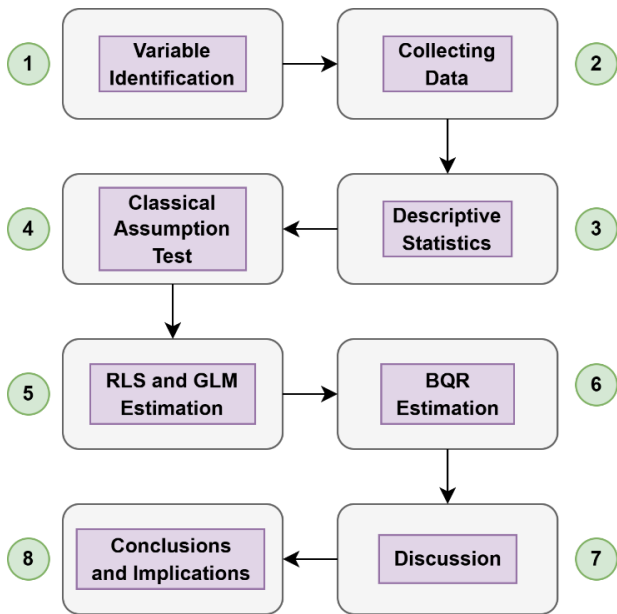


Figure 2. Study's flow analysis.

level corruption experiences serve as the main independent variable, capturing direct exposure to corrupt practices, and additional controls are included to isolate their effect. This approach allows for a rigorous analysis of how micro-level corruption dynamics may inform broader perceptions of corruption at the national level.

2.4.2. Robust Least Squares (RLS)

Robust Least Squares (RLS) is a statistical method designed to address the sensitivity of Ordinary Least Squares (OLS) regression to outliers and violations of classical assumptions such as homoskedasticity and normality [50, 51]. While OLS minimizes the sum of squared residuals, RLS techniques aim to minimize the impact of influential observations that can distort parameter estimates [52–54]. In the context of this study, which examines the impact of firm-level corruption experiences on the CPI, RLS is particularly valuable for ensuring robust estimation, especially given the possibility of data irregularities across countries. By incorporating robustness into the estimation process, RLS provides more reliable coefficient estimates in the presence of data contamination, heavy-tailed distributions, or model misspecification [55, 56].

M-type estimation is a widely adopted technique within the RLS framework. It extends the traditional OLS approach by minimizing a residual-based function that is less affected by extreme deviations. Rather than focusing on minimizing squared residuals, M-estimators apply a specified loss function, $\rho(e)$ —such as the Huber or Tukey biweight function—that limits the impact of outliers on the estimation process. This method preserves high

efficiency when residuals follow a normal distribution while offering improved robustness in the presence of outliers. The degree of robustness can be adjusted through tuning parameters within the loss function, enabling a flexible trade-off between statistical efficiency and resistance to influential observations [57–59].

2.4.3. Bootstrap Quantile Regression

This study also employs quantile regression with bootstrap standard errors to analyze the heterogenous impact of firm-level corruption experiences on the CPI. Unlike Gaussian GLM and RLS, which estimates the conditional mean of the dependent variable, quantile regression allows for the estimation of conditional quantiles, offering a more nuanced understanding of how corruption experiences affect different points in the CPI distribution [56, 60]. This is particularly important for capturing heterogeneity in the relationship across contexts with varying levels of perceived corruption. The analysis focuses on the 0.2 (low), 0.5 (median), and 0.8 (high) quantiles to represent countries with relatively high, moderate, and low levels of perceived corruption, respectively. These specific quantiles are chosen to provide balanced insights across the distribution, identifying whether the effect of firm-level corruption differs in low-CPI countries compared to those with mid-range or high CPI scores. Bootstrap standard errors are used to improve inference reliability, accounting for potential violations of homoscedasticity and distributional assumptions [61, 62].

2.5. Flow Analysis of the Study

The empirical analysis in this study, illustrated in Figure 2, follows a systematic flow, beginning with variable identification, followed by data collection and the presentation of descriptive statistics. The analysis then moves to a preliminary diagnostic phase, which includes three classical assumption tests (normality, multicollinearity, and heteroskedasticity) to ensure the reliability and validity of the estimation models. Subsequently, the study performs regression estimations using three selected methods: Gaussian GLM, RLS, and BQR. The results obtained from these methods are then analyzed and discussed. Finally, the analysis concludes with the study's key findings, practical implications, and suggestions for future research.

3. Results and Discussion

3.1. Descriptive Statistics

Table 2 presents the descriptive statistics for the CPI, BI, GE, and IP variables, providing key insights into corruption perceptions and firm-level corruption

Table 2. Descriptive statistics of raw data.

Variable (Units)	Mean	Median	Max.	Min.	Std. Dev.
CPI (Scale 0-100)	40.42	40	71	20	11.2183
BI (% of Total Firms)	12.59	7.85	34.3	0.9	9.7483
GE (% of Total Firms)	9.71	5.7	35.4	0.3	9.3355
IP (% of Total Firms)	13.64	7.55	46.3	0.1	13.0824
GDPC1 (Constant LCU)	5045430	168160.1	58102617	4423.356	13059564
GDPC2 (Current US Dollar)	8079.373	5133.692	27331.21	495.9789	7722.57
GDPC3 (Current LCU)	8025398	228279.8	1.02E+08	5391.069	21930327

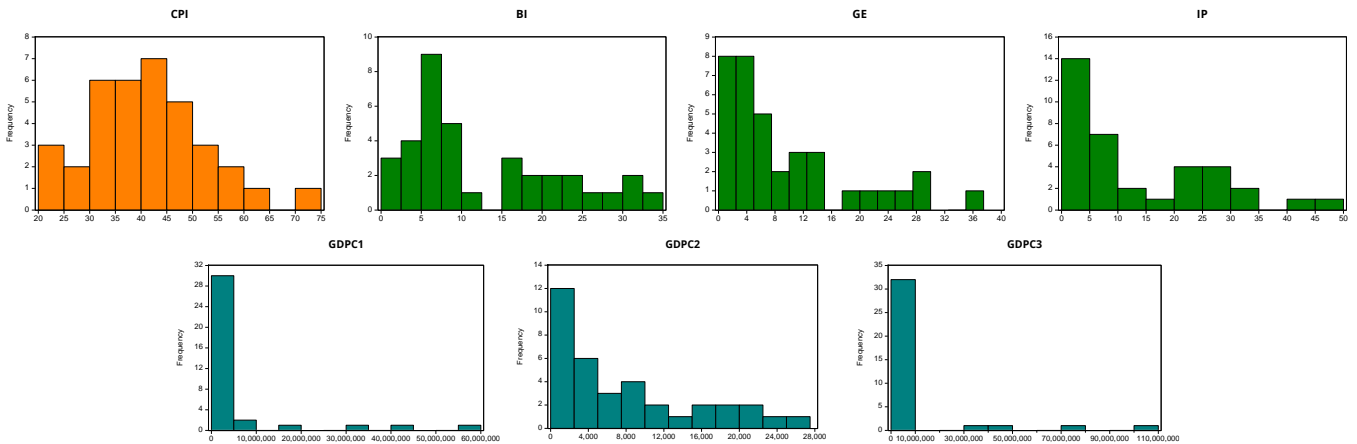


Figure 3. Graphical representation of the raw data distribution through histograms.

experiences across the 36 countries analyzed. The Corruption Perceptions Index (CPI) has a mean of 40.42 and a median of 40, indicating that most countries in the sample are perceived to have relatively high levels of public-sector corruption. The minimum CPI is 20 and the maximum is 71, showing a wide range in perceived corruption levels. For firm-level corruption, the bribery incidence (BI) has a mean of 12.59%, with a substantial standard deviation of 9.75, suggesting considerable variation across countries. Similarly, the percentage of firms reporting gifts to tax officials (GE) averages 9.71%, while informal payments to public officials (IP) averages 13.64%, both also showing high dispersion. The relatively high standard deviations in all three indicators reflect significant cross-country differences in the prevalence of firm-level corruption practices.

In terms of economic control variables, the GDP per capita indicators (GDPC1, GDPC2, and GDPC3) show large disparities across countries. GDPC1, measured in constant local currency units, has a very high mean (5,045,430) but a much lower median (168,160.1), and an extremely wide range from 4,423.36 to over 58 million, with a high standard deviation, indicating severe skewness due to a few high-income countries. GDPC2, expressed in current US dollars, presents a more interpretable mean of \$8,079.37, with a median of \$5,133.69, again reflecting disparities in income levels among countries. Lastly, GDPC3, in current local currency units, shows similar patterns of skewness, with a mean of

8,025,398 and a standard deviation of over 21 million, highlighting the wide variation in economic development levels across the sample. These differences in GDP measures underscore the need to control for economic context when examining the relationship between firm-level corruption and CPI.

Meanwhile, Figure 3 shows the histograms for CPI, BI, GE, and IP, which visually demonstrate the distribution of corruption-related measures. The CPI histogram shows a moderately left-skewed distribution, with most countries scoring between 30 and 50, indicating a general tendency toward moderate levels of perceived corruption. The BI, GE, and IP histograms are right-skewed, showing that the majority of firms in these countries report relatively low incidences of bribe payments, gifts to secure government contracts, and informal payments, though a few countries report much higher levels. These distributions suggest that while corruption is present, extreme cases are concentrated in fewer countries.

The histograms for GDPC1, GDPC2, and GDPC3 display highly skewed distributions, indicating wide disparities in economic development among the countries. The GDPC1 and GDPC3 histograms, measured in local currencies (constant and current), show a heavy right skew, with most countries clustered at the lower end and only a few reaching extremely high levels. The GDPC2 histogram, measured in USD, also reflects this skew, although the spread is less pronounced due to currency standardization. Overall, these distributions highlight the

Table 3. Results of Jarque-Bera normality test.

Model	Main Independent Variable	Control Independent Variable	Jarque-Bera	
			Stat.	Prob.
1	BI	GDPC1	0.6275	0.7307
2	BI	GDPC2	0.5334	0.7659
3	BI	GDPC3	0.6284	0.7304
4	GE	GDPC1	0.5397	0.7635
5	GE	GDPC2	0.6386	0.7266
6	GE	GDPC3	0.4938	0.7812
7	IP	GDPC1	0.2535	0.8809
8	IP	GDPC2	0.3123	0.8554
9	IP	GDPC3	0.2668	0.8751

Note: A probability value >0.05 indicates the residuals are normally distributed; All variables are in their natural logarithmic (ln) form.

Table 4. Results of Pearson correlation test.

Main Independent Variable	Pearson Correlation Coefficient		
	Control Independent Variable		
	GDPC1	GDPC2	GDPC3
BI	0.1573	-0.4831	0.1758
GE	0.1645	-0.3769	0.1752
IP	0.2695	-0.5935	0.3027

Note: A coefficient value <0.7 indicate no multicollinearity; All variables are in their natural logarithmic (ln) form.

Table 5. Results of Breusch-Pagan-Godfrey heteroskedasticity test.

Model	Main Independent Variable	Control Independent Variable	F-stat. (Prob.)	Obs. × R ² (Prob. Chi ²)	Scaled Explained Sum of Squares (Prob. Chi ²)
1	BI	GDPC1	0.7177	0.6989	0.8144
2	BI	GDPC2	0.2717	0.2549	0.4460
3	BI	GDPC3	0.7374	0.7194	0.8286
4	GE	GDPC1	0.3351	0.3154	0.3942
5	GE	GDPC2	0.2927	0.2748	0.4578
6	GE	GDPC3	0.3178	0.2987	0.3811
7	IP	GDPC1	0.9903	0.9894	0.9927
8	IP	GDPC2	0.4309	0.4084	0.5537
9	IP	GDPC3	0.9819	0.9803	0.9863

Note: A probability value >0.05 indicates no evidence of heteroskedasticity; All variables are in their natural logarithmic (ln) form.

significant economic inequality present across the dataset, which could influence the variation in corruption indicators.

3.2. Classical Assumption Test

3.2.1. Normality Test

The normality test assesses whether the residuals from a regression model are normally distributed, which is a key assumption in many linear regression techniques to ensure valid statistical inference [63]. Table 3 presents the results of the Jarque-Bera normality test for nine models, each with different combinations of main independent and control variables. The reported probability values for all models are well above the conventional 0.05 threshold, indicating no evidence to reject the null hypothesis of normally distributed residuals. This suggests that the residuals in all models follow a normal distribution, supporting the validity of the regression estimates under the normality assumption. Consequently, no additional corrective measures for non-normality were required in subsequent analyses.

3.2.2. Multicollinearity Test

The purpose of the multicollinearity test is to determine whether the independent variables in the regression model are highly correlated with one another, as such correlations can lead to inflated standard errors and unreliable coefficient estimates [64]. One way to evaluate this is by analyzing the pairwise correlation coefficients among the independent variables [65]. As presented in Table 4, all main independent and control variables exhibit correlation values below 0.7, indicating an absence of strong linear associations. This finding confirms that multicollinearity is not a major issue and is unlikely to distort the accuracy of the regression outcomes.

3.2.3. Heteroskedasticity Test

In addition to tests for normality and multicollinearity, assessing heteroskedasticity is a key component of the classical linear regression assumptions, as it checks whether the error term variances are consistent across observations, crucial for ensuring efficient and unbiased

Table 6. Gaussian GLM and RLS results for BI's impact on CPI.

Variable	Coeff. (z-stat.)					
	Gaussian GLM			RLS		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
C	-1.1041 (-4.30)*	-2.0513 (-7.05)*	-1.0915 (-4.06)*	-1.0810 (-3.94)*	-2.0465 (-6.53)*	-1.0702 (-3.72)*
BI	-0.1081 (-2.19)**	-0.0380 (-0.77)	-0.1074 (-2.17)**	-0.0979 (-1.85)***	-0.0256 (-0.48)	-0.0974 (-1.84)***
GDPC1	-0.0084 (-0.50)			-0.0083 (-0.47)		
GDPC2		0.1204 (3.11)*			0.1235 (2.96)*	
GDPC3			-0.0089 (-0.52)			-0.0088 (-0.48)

Note: *, **, and *** indicate 1%, 5%, and 10% significance levels, respectively; All variables are in their natural logarithmic (ln) form.

Table 7. Gaussian GLM and RLS results for GE's impact on CPI.

Variable	Coeff. (z-stat.)					
	Gaussian GLM			RLS		
	Model 4	Model 5	Model 6	Model 4	Model 5	Model 6
C	-1.1397 (-4.50)*	-2.0748 (-7.36)*	-1.1249 (-4.26)*	-1.1667 (-4.41)*	-2.0624 (-6.87)*	-1.1595 (-4.19)*
GE	-0.1017 (-2.45)**	-0.0579 (-1.49)	-0.1012 (-2.43)**	-0.1027 (-2.36)**	-0.0547 (-1.32)	-0.1024 (-2.35)**
GDPC1	-0.0075 (-0.46)			-0.0062 (-0.36)		
GDPC2		0.1148 (3.21)*			0.1140 (2.99)*	
GDPC3			-0.0083 (-0.49)			-0.0064 (-0.36)

Note: * and ** indicate 1% and 5% significance levels, respectively. All variables are in their natural logarithmic (ln) form.

estimates [66]. This study uses the Breusch-Pagan-Godfrey test [67] across nine models, each incorporating different main independent and control variables. As shown in Table 5, all p-values for the F-statistic, Obs \times R², and Scaled Explained SS exceed the 0.05 threshold, providing no evidence to reject the null hypothesis of homoskedasticity. This suggests that the error variances are constant across models, and heteroskedasticity is unlikely to bias the regression results.

3.3. Mean-Based Estimation with Gaussian GLM and RLS

3.3.1. Results of BI's Impact on CPI

The first estimation results in Table 6 from the Gaussian GLM and RLS models highlight the effect of BI on the CPI. BI consistently shows a negative relationship with CPI across all model specifications, indicating that higher bribery incidence is associated with greater perceived corruption. BI is statistically significant in Models 1 and 3 under both the Gaussian GLM and RLS approaches. It is significant at the 5% level in the Gaussian GLM and at the weaker but still acceptable 10% level in RLS. Specifically, a 1% increase in BI is associated with approximately a 0.11% decrease in CPI in Model 1 and around a 0.10% decrease in Model 3.

The control variable GDP per capita shows varied effects depending on the measurement used. Only GDPC2 (current US dollars) is statistically significant in both Gaussian GLM and RLS, suggesting that higher income levels, when measured in market terms, are associated with lower perceived corruption. In contrast, GDPC1 (constant LCU) and GDPC3 (current LCU) do not show significant effects, indicating that not all income measures capture the relationship with CPI equally. Meanwhile, the constant term is consistently negative and significant across all models, reflecting a generally high baseline level of perceived corruption when explanatory variables are absent.

3.3.2. Results of GE's Impact on CPI

The results in Table 7 for GE on the CPI using Gaussian GLM and RLS also show a consistent negative relationship, indicating that higher levels of gift expectation are associated with greater perceived corruption. GE is statistically significant at the 5% level in Model 4 and Model 6 under both methods. This pattern mirrors the results found for previous main independent of BI, where the negative impact on CPI was also significant in the models using GDPC1 and GDPC3 as controls, further confirming that informal practices, whether in the form of bribery or gift-giving, consistently

Table 8. Gaussian GLM and RLS results for IP's impact on CPI.

Variable	Coeff. (z-stat.)					
	Gaussian GLM			RLS		
	Model 7	Model 8	Model 9	Model 7	Model 8	Model 9
C	-1.0839 (-4.23)*	-2.0549 (-6.58)*	-1.0818 (-3.97)*	-1.0766 (-3.96)*	-2.0571 (-6.24)*	-1.0778 (-3.72)
IP	-0.0744 (-2.08)**	-0.0086 (-0.23)	-0.0742 (-2.05)**	-0.0726 (-1.92)***	-0.0021 (-0.05)	-0.0725 (-1.89)***
GDPC1	-0.0045 (-0.26)			-0.0044 (-0.24)		
GDPC2		0.1291 (3.04)*			0.1317 (2.94)*	
GDPC3			-0.0044 (-0.25)			-0.0041 (-0.22)

Note: *, **, and *** indicate 1%, 5%, and 10% significance levels, respectively; All variables are in their natural logarithmic (ln) form.

Table 9. Bootstrap quantile regression results for BI's heterogeneous impact on CPI.

Variable	Coeff. (t-stat.)								
	Low-CPI-score countries			Middle-CPI-score countries			High-CPI-score countries		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
C	-1.4680 (-4.19)*	-2.0799 (-3.99)*	-1.4638 (-4.01)*	-1.0206 (-2.97)*	-1.9178 (-4.11)*	-1.0143 (-2.81)*	-1.1270 (-2.38)**	-1.7825 (-4.43)*	-1.0250 (-2.24)**
BI	-0.1523 (-2.63)**	-0.0849 (-1.34)	-0.1519 (-2.63)**	-0.0625 (-0.87)	0.0202 (0.28)	-0.0615 (-0.85)	-0.1403 (-1.08)	-0.0021 (-0.03)	-0.1263 (-1.07)
GDPC1	-0.0048 (-0.20)			-0.0073 (-0.31)			0.0040 (0.15)		
GDPC2		0.0837 (1.19)			0.1255 (2.13)**			0.1210 (2.46)**	
GDPC3			-0.0049 (-0.20)			-0.0072 (-0.31)			-0.0008 (-0.03)

Note: * and ** indicate 1% and 5% significance levels, respectively; Low-CPI-score = 0.2 quantile, Middle-CPI-score = 0.5 quantile, and High-CPI-score = 0.8 quantile; All variables are in their natural logarithmic (ln) form.

reduce perceived integrity. Specifically, a 1% increase in GE is associated with approximately a 0.10% decrease in CPI in Models 4 and 6 under both GLM and RLS.

The control variable GDP per capita again shows varied significance. GDPC2 (current US dollars) remains the only significant income measure in Model 5 for both GLM and RLS, reaffirming that higher income, when measured in current USD, is associated with improved perceptions of corruption. GDPC1 (constant LCU) and GDPC3 (current LCU) do not exhibit significant effects, consistent with previous results. The constant term is negative and statistically significant at the 1% level in all models, indicating a high baseline level of perceived corruption when all independent variables are excluded.

3.3.3. Results of IP's Impact on CPI

The final estimation results from the Gaussian GLM and RLS in Table 8 examine the effect of IP on the CPI and reveal a consistent negative association. Across both models, higher levels of informal payments correlate with greater perceived corruption. IP is found to be significant in Models 7 and 9, at the 5% significance level in GLM and the 10% significance level in RLS. Specifically, a 1% increase in IP is associated with approximately a 0.07%

decrease in CPI. These findings are consistent with earlier results for other firm-level corruption practices, such as bribery incidence and gift expectations, reinforcing the conclusion that informal payments undermine perceived institutional integrity.

Regarding the control variables, GDP per capita again yields mixed results but follows a similar pattern as before. Among the three income measures, only GDPC2 (measured in current US dollars) is statistically significant (in Model 8 under both GLM and RLS) suggesting that higher income levels, when expressed in current USD, are associated with reduced perceptions of corruption. In contrast, GDPC1 (constant LCU) and GDPC3 (current LCU) remain statistically insignificant, consistent with earlier findings. Lastly, the constant term is consistently negative and highly significant at the 1% level across all specifications, indicating a substantial baseline level of perceived corruption even in the absence of explanatory variables.

3.4. Bootstrap Quantile Regression

3.4.1. Results of BI's Heterogeneous Impact on CPI

Table 9 presents the first BQR results, illustrating the heterogeneous effect of BI on the CPI across countries

Table 10. Bootstrap quantile regression results for GE's heterogeneous impact on CPI.

Variable	Coeff. (t-stat.)								
	Low-CPI-score countries			Middle-CPI-score countries			High-CPI-score countries		
	Model 4	Model 5	Model 6	Model 4	Model 5	Model 6	Model 4	Model 5	Model 6
C	-1.4614 (-4.02)*	-2.1717 (-4.49)*	-1.5921 (-3.94)*	-1.0398 (-2.87)*	-1.8316 (-3.93)*	-1.0312 (-2.71)**	-1.0367 (-2.54)**	-1.8175 (-4.31)*	-0.7180 (-1.96)
GE	-0.1199 (-2.26)**	-0.0775 (-1.37)	-0.1318 (-2.39)**	-0.0638 (-0.96)	-0.0123 (-0.20)	-0.0639 (-0.96)	-0.1115 (-1.18)	-0.0349 (-0.56)	-0.0497 (-0.78)
GDPC1	-0.0034 (-0.15)			-0.0075 (-0.33)			0.0005 (0.02)		
GDPC2		0.0954 (1.44)			0.1029 (1.80)***			0.1114 (2.35)**	
GDPC3			0.0027 (0.11)			-0.0078 (-0.34)			-0.0127 (-0.57)

Note: *, **, and *** indicate 1%, 5%, and 10% significance levels, respectively; Low-CPI-score = 0.2 quantile, Middle-CPI-score = 0.5 quantile, and High-CPI-score = 0.8 quantile; All variables are in their natural logarithmic (ln) form.

grouped by corruption levels. In low-CPI-score countries (the most corrupt), BI demonstrates a consistently negative and statistically significant relationship with CPI in Models 1 and 3. Based on the coefficients, a 1% increase in BI reduces the CPI score by approximately 0.15%, indicating that higher levels of bribery are strongly associated with increased perceived corruption in these contexts. This suggests that in more corrupt environments, bribery plays a significant and direct role in shaping negative integrity perceptions. In contrast, among middle-CPI-score countries, the BI coefficients are small and statistically insignificant across all models, implying a weaker or negligible relationship. A similar pattern is observed in high-CPI-score countries, where BI remains negative but insignificant, indicating that bribery has a reduced or unclear impact on perceived corruption in cleaner institutional environments.

Regarding the control variables, GDP per capita shows mixed results, with only GDPC2 (measured in current USD) achieving statistical significance in a few models. Specifically, GDPC2 is significant and positive in Model 2 for middle-CPI-score countries and in Models 2 and 3 for high-CPI-score countries, suggesting that higher income levels are associated with reduced perceptions of corruption in relatively cleaner countries. In contrast, GDPC1 (constant LCU) and GDPC3 (current LCU) remain consistently insignificant across all quantiles, echoing previous findings that their explanatory power is limited. Lastly, the constant term is negative and highly significant at the 1% level in nearly all models, reinforcing the presence of a substantial baseline level of perceived corruption even in the absence of explanatory variables. This result underscores the systemic nature of corruption perceptions, particularly in lower-CPI countries.

3.4.2. Results of GE's Heterogeneous Impact on CPI

The second set of BQR results, presented in Table 10, focuses on the varying effects of GE on the CPI. In low-

CPI-score countries (indicating higher corruption), GE shows a pattern similar to BI, with a consistently negative and statistically significant effect in Models 4 and 6, suggesting that a higher expectation of gifts is associated with increased perceived corruption. The magnitude of the coefficients, where a 1% increase in GE reduces the CPI by approximately 0.12–0.13%, implies that even modest increases in gift-related expectations can meaningfully worsen corruption perceptions in these more corrupt environments. In contrast, for middle- and high-CPI-score countries, the coefficients for GE are negative but statistically insignificant across all models, indicating a weaker or negligible relationship between gift expectations and CPI in less corrupt settings.

The control variable GDP per capita yields varied results across its three forms. GDPC2 (measured in current USD) emerges as statistically significant in Model 5 for both middle- and high-CPI-score countries, with a positive coefficient, implying that higher income levels may contribute to improved corruption perceptions in cleaner institutional environments. Meanwhile, GDPC1 (constant LCU) and GDPC3 (current LCU) remain consistently insignificant, suggesting limited relevance in explaining CPI variation. Additionally, the constant term is negative and statistically significant in nearly all models, particularly in lower-CPI countries, pointing to an inherent baseline level of perceived corruption that persists regardless of explanatory variables.

3.4.3. Results of IP's Heterogeneous Impact on CPI

Table 11 presents the final BQR results analyzing the heterogeneous impact of IP on the CPI across different corruption-level country groups. In low-CPI-score countries, IP exhibits consistently negative coefficients across all models, but these are statistically insignificant, suggesting that informal payments do not have a strong or consistent influence on perceived corruption in these more corrupt settings based on the BQR approach. A

Table 11. Bootstrap quantile regression results for IP's heterogeneous impact on CPI.

Variable	Coeff. (t-stat.)								
	Low-CPI-score countries			Middle-CPI-score countries			High-CPI-score countries		
	Model 7	Model 8	Model 9	Model 7	Model 8	Model 9	Model 7	Model 8	Model 9
C	-1.4632 (-2.49)	-2.8456 (-4.09)*	-1.4638 (-2.41)**	-0.9512 (-2.74)*	-1.8123 (-3.58)*	-0.9357 (-2.53)**	-0.9339 (-3.19)*	-1.7776 (-4.01)*	-0.9182 (-2.93)*
IP	-0.0863 (-1.31)	-0.0009 (-0.02)	-0.0863 (-1.31)	-0.0701 (-0.96)	0.0152 (0.28)	-0.0717 (-0.98)	-0.0844 (-1.39)	-0.0013 (-0.02)	-0.0814 (-1.35)
GDPC1	0.0006 (0.02)			-0.0101 (-0.45)			-0.0041 (-0.20)		
GDPC2		0.1974 (2.28)**			0.1126 (1.68)			0.1206 (1.84)***	
GDPC3			0.0006 (0.02)			-0.0110 (-0.47)			-0.0046 (-0.22)

Note: *, **, and *** indicate 1%, 5%, and 10% significance levels, respectively; Low-CPI-score = 0.2 quantile, Middle-CPI-score = 0.5 quantile, and High-CPI-score = 0.8 quantile; All variables are in their natural logarithmic (ln) form.

similar pattern is observed in middle- and high-CPI-score countries, where the IP coefficients remain negative in most models but continue to lack statistical significance. This indicates that, unlike bribery or gift expectations, informal payments may have a less direct or more diffuse effect on overall corruption perceptions, regardless of a country's corruption level.

Among the control variables, GDP per capita again presents mixed results. GDPC2 (current USD) appears statistically significant in Model 8 for low-CPI-score countries and Model 8 for high-CPI-score countries, with positive coefficients, suggesting that higher income levels are associated with better corruption perceptions in both highly corrupt and cleaner environments, though this effect is less consistent in middle-CPI countries. In contrast, GDPC1 (constant LCU) and GDPC3 (current LCU) remain statistically insignificant throughout, reinforcing earlier findings that their explanatory power is limited. The constant term continues to be negative and statistically significant in most models, further supporting the presence of an underlying baseline level of perceived corruption independent of the observed variables.

3.5. Discussion

This section interprets the empirical findings by synthesizing the results from the Gaussian GLM, Robust Least Squares (RLS), and Bootstrap Quantile Regression (BQR) methods. The discussion highlights the extent to which firm-level corruption, measured through Bribery Incidence (BI), Gift Expectation (GE), and Informal Payments (IP), shapes public perceptions of corruption as captured by the Corruption Perceptions Index (CPI). The results consistently show that all three indicators have statistically significant negative effects on CPI at the mean level. In practical terms, this means that an increase in these corrupt practices at the firm level is associated with a deterioration in a country's perceived integrity, ultimately contributing to worsening corruption

perceptions. However, in terms of heterogeneous effects, only BI and GE show statistically significant impacts in low-CPI-score countries, suggesting varying sensitivity based on a country's existing corruption context.

4.4.1. Bribery Incidence Impact on CPI

Bribery Incidence demonstrates a consistent and statistically significant negative effect on CPI across all mean-based models. Specifically, a 1% increase in BI corresponds to a reduction in CPI scores ranging from 0.0974% to 0.1081%. This finding reinforces the theoretical proposition that routine bribery transactions between firms and public officials are not merely isolated incidents but are perceived as indicators of systemic corruption, thus eroding national governance reputations [14]. These results align with institutional and signaling theories, which emphasize how micro-level corrupt practices reflect systemic weaknesses and shape broader governance assessments [26, 40]. In environments where bribery is prevalent, such behavior is likely interpreted by both domestic observers and international stakeholders as evidence of deeply rooted governance failures [13, 68].

The heterogeneous analysis reveals that the impact of BI is concentrated in low-CPI-score countries, those perceived as more corrupt. In this group, a 1% increase in BI leads to a more pronounced decline in CPI, ranging from 0.1519% to 0.1523%. The larger effect in these contexts suggests that bribery is not only more prevalent but also more consequential for national integrity perceptions. This result supports the signaling hypothesis: in already fragile institutional environments, observed firm-level corruption serves as a credible signal of broader governance failures to external stakeholders [26, 40]. In contrast, the non-significant results for middle- and high-CPI-score countries suggest a threshold effect, wherein bribery loses explanatory power for CPI variation once a country has established relatively higher

institutional credibility [69]. This indicates that in more transparent environments, occasional instances of bribery may be perceived as outliers rather than systemic features.

4.4.2. Gift Expectation Impact on CPI

Gift Expectation to tax officials also exerts a statistically significant and negative impact on CPI. Across the mean-based estimations, a 1% increase in GE is associated with a CPI reduction ranging from 0.1012% to 0.1027%, underscoring how expectations of unofficial gifts can diminish perceived public-sector integrity. This finding suggests that informal gift-giving, though sometimes perceived as culturally embedded or benign, is interpreted by external evaluators as indicative of institutional opacity and favoritism [70]. The negative implications are especially pertinent in tax administration, where perceptions of fairness and transparency are critical to public trust and fiscal legitimacy [71, 72].

The quantile analysis underscores that this GE effect is similar with BI which particularly salient in low-CPI-score countries, where a 1% increase in GE is associated with a 0.1199% to 0.1318% decline in CPI. This finding suggests that expectations for gifts are especially damaging to a country's corruption reputation when institutional frameworks are already perceived as weak [73]. The normalized presence of such expectations implies entrenched informal norms within tax administration, further eroding trust in public financial management [74]. Meanwhile, in middle- and high-CPI-score countries, GE's effect becomes statistically insignificant, which could imply that in contexts where institutional quality is relatively strong, minor or isolated gift expectations do not substantially shift overall corruption perceptions. This again highlights the importance of contextualizing micro-level behaviors within broader institutional settings when evaluating their impact on national governance metrics [75].

4.4.3. Informal Payments Impact on CPI

Informal Payments to public officials show a significant negative effect on CPI in the mean-based estimations, with a 1% increase in IP leading to a reduction in CPI scores between 0.0725% and 0.0744%. Although the magnitude is slightly smaller than those of BI and GE, the direction and significance of the relationship reinforce the overall argument that firm-level corruption systematically deteriorates national corruption perceptions [8]. This suggests that even less visible or routine unofficial transactions can meaningfully undermine a country's perceived institutional credibility [15, 76].

However, the quantile regression results reveal that IP lacks significant heterogeneous effects across all corruption contexts: low, middle, and high CPI-score countries. This suggests that, while IP reduces CPI scores on average, its influence is more diffuse and not particularly context-sensitive. One possible explanation is that informal payments may be more ambiguous in terms of intent or visibility, making them less potent signals of systemic corruption in the eyes of international observers [77]. Alternatively, the nonsignificant heterogeneous results may reflect measurement limitations, such as variations in how firms interpret or report informal payments across countries [78]. Regardless, the consistent mean-level impact implies that efforts to reduce informal payments remain critical for enhancing a country's overall reputation for integrity.

4. Conclusions, Implications and Directions for Future Research

The findings of this study confirm that firm-level corruption, measured through bribery incidence, gift expectations to tax officials, and informal payments, exerts a significant and negative impact on a country's Corruption Perceptions Index (CPI). In this context, it means that increases in these practices are statistically proven to lower CPI scores, indicating that more frequent corruption at the firm level leads to worse public perceptions of corruption. While all three forms of firm-level corruption reduce CPI scores on average, the effects of bribery and gift expectations are particularly pronounced in countries already perceived as highly corrupt, highlighting the context-sensitive nature of their influence. These results underscore the importance of micro-level business practices in shaping national integrity assessments and reinforce the relevance of institutional and signaling theories in explaining how localized corrupt behavior reflects and reinforces broader governance failures.

The results hold significant implications for businesses, especially those operating in or expanding into emerging markets. Engaging in corrupt practices, even when normalized, can have reputational consequences beyond the firm level, as they contribute to negative perceptions of national integrity. Companies should invest in internal compliance systems, adopt clear anti-bribery policies, and train employees to avoid informal transactions with public officials. Beyond risk mitigation, firms that promote ethical conduct and transparency can position themselves as credible actors in the market and may benefit from improved investor confidence and stronger relationships with regulatory institutions.

For policymakers, the findings suggest that reducing routine corruption in business–government interactions should be a central component of national anti-corruption strategies. The disproportionate impact of bribery and gift expectations in low-CPI-score countries indicates that efforts to restore trust in public institutions must begin with curbing everyday transactional corruption. Strengthening enforcement mechanisms, increasing transparency in tax and licensing processes, and fostering a zero-tolerance culture toward informal exchanges can collectively improve institutional credibility. Moreover, monitoring and publicly reporting firm-level corruption metrics may serve as an early-warning system to identify areas of governance vulnerability before they escalate into systemic issues.

Lastly, this study acknowledges several limitations that present opportunities for future research. First, the analysis relies solely on cross-sectional data, which limits the ability to capture temporal dynamics or country-specific trends; future studies should consider using time-series or panel data to explore changes in firm-level corruption and CPI over time. Second, the study employs a static econometric framework, which, while robust, does not account for potential long-run relationships or feedback effects; future research could apply dynamic models such as the Autoregressive Distributed Lag (ARDL) approach or cointegrating regression techniques to better capture these complexities. Third, due to data availability constraints, the analysis focuses on only three firm-level corruption indicators; future work should incorporate additional or alternative indicators as more comprehensive data become available, allowing for a broader understanding of how various forms of firm-level corruption influence public perceptions.

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