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Public Sector Corruption and the Valuation of Systemically Important Banks

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Abstract

We relate the valuation dynamics of global systemically important banks (G-SIB) to levels of public sector corruption in their country of domicile. We show that G-SIB valuations benefitted from higher perceived public sector corruption before the global financial crisis (1998:Q1-2007:Q2), but not during or after the crisis (2007:Q3-2018:Q1). We interpret this as evidence of a corruption-related hidden subsidy in the valuation of G-SIBs before the crisis, which is reversed after the crisis. Corruption affects the transmission channels of bank characteristics to Price-to-Book (PB) valuation ratios both through negative and positive indirect effects. We provide evidence that the corruption-related distortions of level playing field before the crisis were primarily attained through the leverage channel. The sensitivity of PB to earnings risk increases with corruption and this is particularly evident post-crisis. Higher corruption leads to a dwindling pass-through to PB of dividend payout ratios, growth rates in GDP, and expected net-income.

JEL classifications: C23; D73; G21; G28

Keywords: Bank valuation; Bounds testing; Corruption; G-SIBs; Panel cointegration

1. Introduction

After more than three decades of efforts in the Basel Committee on Banking Supervision (BCBS) to create a unified international set of rules for systemically important banks, global level playing field for bank cost of capital continues to be an issue. Bank valuations could be affected by the quality of public institutions, supervisory conduct and, in particular, perceptions – or misconceptions – of corruption entrenchment in the official sector. In this paper we relate the dynamics of banks' price-to-book ratios to perceptions about public sector corruption in their countries of domicile. We focus on listed banks with assigned status of Global Systemically Important Banks (G-SIBs) by BCBS and Financial Stability Board (FSB). Country scores for public sector corruption are based on the Corruption Perceptions Index (CPI) published by Transparency International.

We show that G-SIB valuations benefitted from higher perceived public sector corruption before the global financial crisis (1998:Q1-2007:Q2), but not during or after the crisis (2007:Q3-2018:Q1). For example, keeping other things constant, a migration from low corruption quartile 1 to medium-high corruption quartile 3 would lead to an average increase in fundamental PB by 0.58 pre-crisis, whilst to an average decline of -0.15 post-crisis. We interpret this as evidence of a corruption-related hidden subsidy in the valuation of G-SIBs before the crisis, which is reversed after the crisis. We provide evidence that such a hidden subsidy is primarily attained through the leverage channel. In other words, in the run up to the global financial crisis, leverage mobilization by G-SIBs in countries with higher levels of corruption played a significant role in distorting the level playing field with respect to bank valuations.

The reversal of the overall effect of corruption on G-SIBs valuation – from positive before crisis, to negative during and after crisis – is primarily driven by a substantial weakening of the leverage channel. Specifically, among bank characteristics, leverage shows the largest drop in economic effect on G-SIBs' valuation between the two periods, and that drop increases with corruption levels. The weakening of the leverage channel could be attributed to significant deleveraging of the banking system due to large scale recapitalizations and tighter capital standards, especially for systemically important banks. It could also be a result of market re-appraisal of earnings risk stemming from higher leverage. In fact, the valuation effect of earnings risk turns out to be negative and significant after the crisis, and even more so as corruption increases. In other words, sensitivity to earnings risk increases with corruption and this is particularly evident post-crisis.

Banks are notoriously difficult to value on the basis of free cash flows because their business models rely on intermediating deposit taking and lending, subject to regulatory constraints about capital structure and asset composition (Damodaran 2012). Moreover, banks are typically excluded from Fama-French type models since leverage is part of their business model, while for non-financial firms leverage is key indicator of financial distress. We follow Bertsatos and Sakellaris (2016) and Bertsatos et al. (2017) and use a dynamic dividend discount (3D) model to establish a fundamental relationship of PB with bank riskiness, growth, and cash flows, while controlling for bank size, leverage, opacity, and general macroeconomic conditions. We allow for transitory deviations from equilibrium and interaction (indirect) effects of corruption with bank characteristics, while controlling for possible changes in valuation dynamics around the global financial crisis.

As the corruption index is based on survey data, it may be affected by time-varying economic conditions, or time-invariant components such as fixtures of governance, the political economy of national banking systems and other cultural characteristics (Uslaner and Rothstein, 2016; Grossman and Woll, 2014; Fisman and Miguel, 2007). We isolate the effect of corruption on bank valuations after controlling for global trends and time-invariant components, as well as for country-specific economic conditions.

The relatively large panel of G-SIBs in the sample allows us to employ ARDL model estimation as a workhorse for analysing valuation dynamics using a two-way dynamic fixed-effect estimator. As a first step, we establish if a long-term relationship between PB and covariates actually exists using a panel bounds testing procedure similar to Bertsatos et al. (2022b) that extends Pesaran et al. (2001). We witness a more sluggish convergence to equilibrium as corruption increases. Especially for the period before the crisis, high levels of corruption lead to a decoupling of PB from fundamentals, but the equilibrium relationship is restored in the aftermath of the crisis.

Corruption (GC) affects the transmission channels of bank characteristics (X) to PB both through negative and positive indirect effects. Its indirect effect ($\partial^2 PB/\partial X \partial GC$) is positive through the leverage channel over the entire sample period, although it weakens in the aftermath of the global financial crisis. This indicates a heightened role of leverage in boosting PB in higher corruption countries, especially in the pre-crisis period. On the other hand, corruption impacts negatively on PB through the dividend payout ratio (DPR) channel, which is suggestive of a declining pass-through of DPR to PB as corruption increases. We also document a negative effect of corruption when interacted with bank size, indicating that corruption induces diseconomies of scale or scope.

The indirect effect of corruption also becomes negative post-crisis in interaction with expected growth in net income, earnings risk, opacity, and GDP growth. In fact, the market seems to reward expected growth in net income only in low corruption countries. For high levels of corruption, concerns about excessive risk-taking appear to dominate and the effect of earnings risk becomes more negative (and significant). Corruption weakens the negative effect of opacity on PB over the short-run, implying that transparency is less rewarded by the market as corruption increases. But in the long-run, the well documented betting-against-beta market anomaly dominates (Frazzini and Pedersen, 2014) given the positive effect of opacity and its strong positive correlation with stock beta. Finally, the positive effect of GDP growth on PB declines with corruption, in line with the dwindling pass-through of DPR and of expected growth in net income.

With the estimated ARDL model for PB dynamics in hand, we run hypothetical scenarios where banks migrate from the corruption level in their country of domicile to higher or lower corruption quartiles, keeping all other characteristics constant. This counterfactual exercise makes it possible to measure the overall effect of corruption on bank valuations and to attribute this effect to various channels. As mentioned before, the evidence from such an exercise points to a corruption-related hidden subsidy in the valuation of G-SIBs before the crisis, which is reversed after the crisis.

A particular econometric concern is that of endogeneity of the bank characteristics and controls used in our models of dynamic PB valuation of banks. To address this potential problem we allow for endogenous regressors using the error-projection mechanism popularized by Cho et al. (2015), Shin et al. (2014), Pesaran et al. (2001), Pesaran and Shin (1999). Our results, presented in the Appendix, demonstrate robustness to short-run reverse causality and strengthen our interpretations of the driving mechanisms of the effects of corruption on bank valuation.

To our knowledge, our paper is the first to provide evidence on the relationship between bank valuation and public-sector corruption. This is an important issue for market participants and regulators. Although bank capital buffers have improved substantially over the past decade, non-regulatory indicators based on market measures – notably the price-to-book ratio – imply a deterioration in bank solvency (Bostandzic et al., 2021; Sarin and Summers, 2016). This led to calls for capital-neutral rules going forward and shifted the policy debate towards rules implementation. For example, recent rules by the FSB for the Total Loss Absorbing Capacity (TLAC) of systemically important banks are implemented in a non-synchronous fashion across counties. Moreover, FSB rules relating to banks' recovery and resolution plans (RRPs) draw on the effectiveness of supervision and the quality of public institutions.

Concerns about public sector corruption could arise from fixtures of governance and the political structure of banking systems that vary across countries. These include government connections and repeated trips through the *revolving door* between the public and private sector, lobbying practices, financing of political campaigns, government involvement in bank operations, and rent-seeking behaviour. Such concerns may be aggravated by large-scale bailouts of banking institutions to deal with the fallout of the global financial crisis and the design of burden-sharing of relevant costs between the public and private sector. This was coupled by extraordinary open market operations by central banks – such as asset purchase programs and long-term refinancing operations – often seen as last resort bailouts of the banking system by stealth.

From a theoretical point of view, perceptions about public sector corruption could have both a positive and a negative effect on price-to-book ratios. On the one hand, politically connected firm's human capital and ideas may feed directly into policy preferences and design (*cultural capture*) that in periods of stress could reduce uncertainty about public policy (Acemoglu et al., 2016; Baker et al., 2016; Gropper et al. (2013); Pástor and Veronesi, 2012; Veronesi and Zingales, 2010; Faccio, 2006; Fisman 2001). In the same vein, lobbying may enhance firm value by influencing uninformed policymakers, thus reducing firm-specific policy uncertainty (Borisov, 2016). From a social network perspective (Brass et al., 1998) firms may also view public sector corruption as an opportunity to sustain competitive advantages and enhance shareholder value (Collins, 2009; Oliver 1997). On the other hand, connections with government officials may facilitate investor expropriation by means of self-dealing (*tunneling*) by corporate insiders. In that sense, public sector corruption could undermine corporate governance and erode firm value (Brown et al. 2021; Dass et al. 2016; Djakov et al., 2008; Dyck and Zingales, 2004; Shleifer and Vishny, 1993; Rose-Ackerman, 1975). Last but not least, direct involvement of government officials in day-to-day bank operations could distort loan pricing and the allocation of financial resources (Houston et al., 2014; Park, 2012; Claessens et al., 2008; Dinc, 2005; Khwaja and Mian, 2005; Sapienza, 2004; La Porta et al., 2002; Laeven, 2001).

The rest of the paper is organized as follows. Section 2 discusses the data and variable defections. Section 3 reviews the empirical strategy and model specification, and Section 4 presents estimation results. Section 5 conducts counterfactual experiments to gauge the overall effect of corruption on bank valuations and its decomposition into various channels. Section 6 concludes. Controls for endogeneity and technical details of the bounds testing procedure used to establish long-run effects are gathered in the Appendix.

2. Data and variables

2.1. Sample banks

We consider all banks that have been assigned the status of Global Systemically Important Banks (G-SIBs) by the Basel Committee on Banking Supervision (BCBS) since 2014 when G-SIB classification by BCBS was initiated. This cohort also includes all banks classified as G-SIBs by the Financial Stability Board (FSB) since 2011, with the exception of Dexia that we also include in the sample for completeness. Therefore, the initial sample covers 102 banks of which 87 listed and 15 unlisted. For these banks we obtain quarterly financial statements and pricing information from Thomson-Reuters Datastream for the period 1998:Q1 to 2018:Q1.[1]

Since we are interested in the price-to-book (PB) ratio we focus on listed banks. We also exclude banks with less than 20 data points in variables of interest. As a result, the final sample consists of 77 institutions from 21 countries.[2] Table 1 shows all G-SIBs in the initial sample by country of domicile and the final sample used in estimations that includes only listed G-SIBs with at least 20 observations.

[Table 1 about here]

We follow the dynamic dividend discount (3D) model of Bertsatos et al. (2017) decomposing PB into three fundamental factors – i.e. risk, growth, and cash flows – to examine the possible impact of public sector corruption on bank valuations. Furthermore, we control for bank size, book leverage and opacity.

Bank-level variables are reported at the highest level (bank holding company) of bank corporate structure and pricing data refer to primary listing. Country-level (macro) variables are also downloaded from Thomson-Reuters Datastream. We also obtain data on the US equity risk premium, the 10-year Treasury bond yield and the domicile country-risk equity premium from Damodaran's website to calculate the cost of equity, as we discuss in the following section.[3]

2.2. Variable definitions

Country scores for public sector corruption are based on the Corruption Perceptions Index (CPI) published by Transparency International, ranging between 0 (highest corruption) and 100 (lowest corruption).[4] CPI for each country is published on annual frequency at the start of next year. Since we work with quarterly

[1] The annual list of G-SIBs is available at the BCBS/BIS and FSB websites.

[2] As a frame of reference, these 77 institutions have total assets of more than 89% of world GDP at end-2017.

[3] For the country-risk equity premium data are available since 2000. For years 1998 and 1999 we assign the same value as for the year 2000. Given also that the country-risk equity premium and the US equity risk premium are available on an annual frequency we convert to quarterly frequency using linear interpolation.

[4] CPI was ranging between 0 (highest corruption) and 10 (lowest corruption) until 2011, with a precision of one decimal point. To make these values comparable with the rest of the sample period we multiply by ten.

data, we set the CPI in the fourth quarter equal to its reported value for the year, while for the previous three quarters we use linear interpolation.[5]

As public sector corruption variable (GC) we use the following transformation of CPI that normalizes corruption scores to be symmetric around zero and increases in corruption level:

$$GC = ln\left(\frac{101-CPI}{CPI}\right) \tag{1}$$

Table 2 maps domicile countries of banks in the final sample to corruption quartiles before and after the crisis. Given that CPI is based on survey data it may be driven by time-varying economic conditions, or time-invariant components such as deeply rooted cultural effects. To isolate possible effects of public sector corruption on bank valuations we include country-specific macroeconomic variables to control for economic conditions, and time fixed effects to remove global trends. We also use bank fixed effects to purge time-invariant components.

[Table 2 about here]

Definitions of bank-specific variables are given next where the corresponding Datastream field codes are shown in square brackets. All bank-specific ratios are expressed in percentages.

Price-to-book (PB) is defined as the ratio of market value of common equity to its book value [WC03501A]. Market value of equity is equal to the unadjusted price [UP] times the number of common shares [NOSH].[6]

With respect to bank *risk* characteristics we use the cost of equity to control for market riskiness and the historical (eight-quarter rolling, including current) volatility of return-on-equity as a measure of earnings risk (sigma RoE).[7] Cost of equity (COE) is calculated in USD terms for bank *i* of country *j* at period *t* as the risk-free rate R_f (proxied by the 10-year Treasury bond yield) plus beta (β) multiplied by the US equity-risk premium, plus the country-risk equity premium CREP.

$$COE_{i,t,USD,j} = R_{f,t,USA} + \beta_{i,t} \cdot ERP_{t,US} + CREP_{t,j} \tag{2}$$

We convert COE in equation (2) in local currency terms using the international Fisher effect.[8]

[5] As an alternative to CPI we considered the variables "Control of Corruption", "Regulatory Quality", and "Government Effectiveness" from the World Bank. These are reported on annual frequency but have missing values for the years 1997, 1999, and 2001. We applied linear interpolation to fill the missing years and converted to quarterly frequency as with CPI. The results were qualitatively unaltered. This was to be expected, given that the annual correlation between CPI and the above World Bank variables is more than 93% across countries in the sample. We chose to stick with CPI as a measure of public sector corruption.

[6] Especially for UK banks, prices are not given in currency units (pound sterling) but in pence. Therefore, we divide market value of common equity by 100 to make it comparable with book value.

[7] As alternative measures of bank risk characteristics we also considered the (ln) z-score, the maximum probability of default, and the (eight-quarter rolling) standard deviation of RoE over an eight-quarter-ahead horizon.

[8] For inflation we use the quarterly growth rate in the 4-quarter moving average consumer price index (PI) $inflation_t = \frac{\sum_{j=-3}^{0} PI_{t+j}}{\sum_{j=-4}^{-1} PI_{t+j}} - 1.$

$$COE_{i,t,j} = \left(1 + COE_{i,t,USD,j}\right) \cdot \frac{1+inflation_{t,j}}{1+inflation_{t,USA}} - 1 \quad (3)$$

To calculate beta at the end of each quarter we regress bank-specific returns on market portfolio returns and a constant using the last 60 month-end observations. Since we have a global sample of banks we use as a proxy for the market portfolio the S&P Global index. For bank-specific and market portfolio returns we use the total return index [RI].[9]

As a proxy for *growth* we use the expected growth of net income (expected growth) defined as the product of the return on common equity (RoE) and the retention ratio (RR). RoE is the ratio of net income available to common shareholders [WC01751A] divided by the lagged book value of common equity [WC03501A]. RR is the part of net income available to common shareholders [WC01751A] that is retained by the firm and defined as RR=1-DPR/100.

For *cash flows* we use the dividend payout ratio (DPR) which is defined as the anticipated dividend on common stock over the following 12 months divided by the book value of common equity [WC03501A]. Anticipated dividend on common stock is calculated as the current annualised dividend per share [DPSC] multiplied by the current number of shares [NOSH].[10]

Leverage is the ratio of book value of assets [WC02999A] to book value of common equity [WC03501A]. We also define bank size as the natural logarithm of book value of assets [WC02999A] in USD and current prices. We use nominal exchange rates to convert book value of assets from local currency to USD. Nominal exchange rates are quarterly averages of daily rates.

Opacity is defined as a measure of market synchronicity by taking the logistic transform of R^2 from monthly market model regressions that we used for beta, in line with Jones et al. (2013) and Bertsatos et al. (2017).

$$OPACITY_{i,t} = ln\left(\frac{R^2}{1-R^2}\right) \quad (4)$$

Dummy variable BC indicates the period "before crisis" (1998:Q1-2007:Q2) and dummy variable DAC the period "during and after crisis" (2007:Q3-2018:Q1). Finally, to control for country-specific economic conditions we use GDP growth as a proxy for the business cycle, the ratio of government debt to GDP to capture public sector indebtedness, the ratio of fiscal balance to GDP as a measure of government's fiscal position, and GDP per capita as a measure of income level.

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[9] Alternatively, we calculate beta using the quarterly average of monthly betas obtained from rolling regressions over the last 60 month-end observations. Yet alternative beta series have more than 99% linear correlation.

[10] We tried alternative variables for dividend payouts, such as "cash dividends paid" [WC04551A], "dividends" [WC04052A], and "common dividends" [WC05376A]. However, for our international sample all these variables suffer from a large number of missing values.

Bank-specific ratios are winsorized at the 0.5th and 99.5th percentile of the sample distribution. Especially for the cost of equity, winsorization is performed using the beta variable, and for earnings risk using the RoE variable. We also drop observations with negative book common equity.[11]

[Table 3 about here]

Table 3 presents descriptive statistics of variables per corruption quartile for the period "before crisis" (Panel A) and "during and after crisis" (Panel B). PB appears to decline with corruption, with an exception before the crisis where it peaks in quartile 2. Also the variability of PB seems to increase with corruption. Similarly, bank riskiness increases with corruption, both in terms of market riskiness (cost of equity) and the historical volatility of return-on-equity (sigma RoE). However, higher PB in low corruption quartiles appears to come at a cost of higher capital distributions (dividend payout ratios) to shareholders. Notice that dividend payout ratios fall from 6.35% (6.96%) of common equity in corruption quartile 1 (2) to 5.16% (2.76%) in quartile 3 (4) before the crisis. A similar pattern obtains with respect to market synchronicity (opacity) that appears to fall with corruption. Observed patterns for expected growth, leverage, and size with respect to corruption are more ambiguous. These observations may indicate a corruption-dependent response of price-to-book to fundamentals, prompting our modeling choice in the following section.

3. Model specification

We use an autoregressive distributed lag (ARDL) model that allows for a mixture of $I(0)$ and $I(1)$ regressors, permitting examination of both short- and long-run effects on price-to-book (Pesaran et al. 2001). We start from a panel ARDL(1,**1**) model in levels for bank i in time t with only direct effects on price-to-book (PB).

$$PB_{i,t} = \lambda \cdot PB_{i,t-1} + a_0 \cdot GC_{i,t} + a_1 \cdot GC_{i,t-1} + \boldsymbol{\beta}_0 \cdot \boldsymbol{X}_{i,t} + \boldsymbol{\beta}_1 \cdot \boldsymbol{X}_{i,t-1} + c + c_i + c_t + u_{i,t} \tag{5}$$

where, λ is autoregressive parameter, $\boldsymbol{X}_i$ is vector of controls, GC_i the corruption variable we define later, $a_0, a_1, \boldsymbol{\beta}_0$, $\boldsymbol{\beta}_1$ are loading factors, c_i, c_t are bank and time effects, c is constant and u_i is the error structure.

Lagged variables address serial correlation in the error term, bank effects eliminate estimation bias due to omitted time-invariant factors, and time fixed effects deal with possible cross-sectional dependence.

Equation (5) is equivalent to a panel ARDL (0,**0**) in unrestricted error-correction form as follows.

$$\Delta PB_{i,t} = \varphi \cdot PB_{i,t-1} + \alpha_0 \cdot \Delta GC_{i,t} + \boldsymbol{\beta}_0 \cdot \Delta \boldsymbol{X}_{i,t} + \alpha \cdot GC_{i,t-1} + \boldsymbol{\beta} \cdot \boldsymbol{X}_{i,t-1} + c + c_i + c_t + u_{i,t} \tag{6}$$

where, Δ denotes first differences, $\alpha = (\alpha_0 + \alpha_1)$, $\boldsymbol{\beta} = (\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1)$, $\varphi = (\lambda - 1)$ is the error-correction parameter, $-\varphi$ is the speed of adjustment, α_0 and $\boldsymbol{\beta}_0$ capture short-term effects, and $-\alpha/\varphi$, $-\boldsymbol{\beta}/\varphi$ are long-run effects. We will refer to this as Model 1.

Equation (6) implies a stable long-run relationship of price-to-book with covariates only if φ takes values in the range (-2, 0). For the existence of a long-term relationship we use a panel extension of the bounds testing procedure of Pesaran et al. (2001), as discussed in Section 4.

[11] As a result of the positive-equity filter we drop 10 observations from the final sample.

To control for a structural break around the global financial crisis we include interactions with dummies for the periods "before crisis" (BC) and "during and after crisis" (DAC). We will refer to this as Model 2:

$$\Delta PB_{i,t} = BC \cdot \left[\varphi_{BC} \cdot PB_{i,t-1} + \alpha_{0,BC} \cdot \Delta GC_{i,t} + \boldsymbol{\beta}_{0,BC} \cdot \Delta \boldsymbol{X}_{i,t} + \alpha_{BC} \cdot GC_{i,t-1} + \boldsymbol{\beta}_{BC} \cdot \boldsymbol{X}_{i,t-1} + c_{BC}\right] + DAC \cdot \left[\varphi_{DAC} \cdot PB_{i,t-1} + \alpha_{0,DAC} \cdot \Delta GC_{i,t} + \boldsymbol{\beta}_{0,DAC} \cdot \Delta \boldsymbol{X}_{i,t} + \alpha_{DAC} \cdot GC_{i,t-1} + \boldsymbol{\beta}_{DAC} \cdot \boldsymbol{X}_{i,t-1} + c_{DAC}\right] + c_i + c_t + u_{i,t} \tag{7}$$

We further include interaction effects of covariates with GC_i to capture corruption-dependent responses of price-to-book to fundamentals.

$$\Delta PB_{i,t} = BC \cdot \left[\varphi_{BC} \cdot PB_{i,t-1} + \varphi_{1,BC} \cdot GC_{i,t} \cdot PB_{i,t-1} + \alpha_{0,BC} \cdot \Delta GC_{i,t} + \boldsymbol{\beta}_{0,BC} \cdot \Delta \boldsymbol{X}_{i,t} + \boldsymbol{\gamma}_{0,BC} \cdot GC_{i,t} \cdot \Delta \boldsymbol{X}_{i,t} + \alpha_{BC} \cdot GC_{i,t-1} + \boldsymbol{\beta}_{BC} \cdot \boldsymbol{X}_{i,t-1} + \boldsymbol{\gamma}_{BC} \cdot GC_{i,t} \cdot \boldsymbol{X}_{i,t-1} + c_{BC}\right] + DAC \cdot \left[\varphi_{DAC} \cdot PB_{i,t-1} + \varphi_{1,DAC} \cdot GC_{i,t} \cdot PB_{i,t-1} + \alpha_{0,DAC} \cdot \Delta GC_{i,t} + \boldsymbol{\beta}_{0,DAC} \cdot \Delta \boldsymbol{X}_{i,t} + \boldsymbol{\gamma}_{0,DAC} \cdot GC_{i,t} \cdot \Delta \boldsymbol{X}_{i,t} + \alpha_{DAC} \cdot GC_{i,t-1} + \boldsymbol{\beta}_{DAC} \cdot \boldsymbol{X}_{i,t-1} + \boldsymbol{\gamma}_{DAC} \cdot GC_{i,t} \cdot \boldsymbol{X}_{i,t-1} + c_{DAC}\right] + c_i + c_t + u_{i,t} \tag{8}$$

where, $\varphi_{1,j}$, $\boldsymbol{\gamma}_{0,j}$, $\boldsymbol{\gamma}_j$ for $j = BC, DAC$ correspond to interaction (indirect) effects of corruption. We will refer to this as Model 3.

Next we present estimation results for direct and indirect effects of corruption on price-to-book. Bounds testing techniques are used for the existence of a long-term relationship of PB with covariates.

4. Estimation results

We perform ARDL model estimation using the two-way dynamic fixed-effect estimator, which is consistent given the relatively large time and cross-sectional dimension of our dataset (Nickell, 1981).

Before analysing estimation results we establish if a long-term relationship between PB and covariates actually exists. Yet for lagged levels standard inference does not apply as they include mixtures of $I(0)$ and $I(1)$ variables. Therefore, for the existence of a long-term relationship we use the panel bounds testing procedure of Bertsatos et al. (2022b) that extends the bounds testing procedure of Pesaran et al. (2001) for time series, as discussed in Appendix B.[12]

Table 4 presents estimation results for all three unrestricted error-correction models in equations (6), (7) and (8) in Section 3, henceforth Models 1, 2 and 3 respectively. Results show that statistically significant direct effects on PB preserve their sign across model specifications, notwithstanding interaction (indirect) effects of corruption. We take this as an indication of results stability across specifications.

[Table 4 about here]

In addition, we allow for endogenous regressors in Model 3 using the error-projection mechanism popularized by Cho et al. (2015), Shin et al. (2014), Pesaran et al. (2001), Pesaran and Shin (1999). As discussed in Appendix A, this is equivalent to augmenting Model 3 with extra lags. Table A.1 demonstrates robustness to short-run reverse causality given trivial differences in statistical significance of estimated coefficients between the two specifications.

[12] Statistical inference for first differences (short-run effects) and constant terms is based on standard methods.

4.1. Characteristics effects

In line with valuation theory, Models 1 and 2 suggest that higher DPR is associated with an increase in PB. But Model 3 indicates the DPR pass-through to PB falls with corruption, as shown by the negative interaction both in the short-run (-0.017 for BC; -0.013 for DAC) and the long-run (-0.010 for BC; -0.004 for DAC). In other words, the effectiveness of dividend payouts to boost PB falls as corruption increases.

Expected growth in net income appears to have no effect on PB before crisis. Surprisingly, the effect turns out to be negative (rather than the expected positive) during and after crisis, especially in the long-run (Model 2). This negative effect is driven primarily by high corruption regimes in Model 3, as indicated by the negative interaction both in the short-run (-0.007 for DAC) and the long-run (-0.008 for DAC). In particular, for low levels of corruption the effect of expected growth is positive, while for high corruption levels it turns out to be negative. We discuss this in more detail in Section 4.3 where we present marginal effects by corruption quartiles.

Cost of equity is found to have a negative short-run effect on PB, mainly in the period during and after crisis (Model 2). The long-run effect of cost of equity appears to be statistically significant (and negative) only before crisis. Overall, the short-run and long-run effects of cost of equity fade out once corruption interactions are taken into account (Model 3). In that case, earnings risk prevails as a risk measure, as we discuss in more detail in Section 4.3 where we show marginal effects by corruption quartiles.

Regarding earnings risk (sigma RoE), both its short-run and long-run effects on PB are statistically significant (and negative) in Models 1 and 2. Especially in the short-run, this negative effect is exacerbated by corruption (Model 3) given the negative interaction effects (-0.040 for BC; -0.013 for DAC). In other words, the market appears to become more sensitive to earnings risk as corruption increases.

Leverage appears to have a positive impact on PB both in the short-run and long-run in all model specifications. But the positive effect of leverage on PB weakens during and after crisis, in line with evidence for large US banks by Calomiris and Nissim (2014). The weaker effect of leverage on PB could result from tighter capital standards and market re-appraisal of RoE risk associated with higher leverage. This is consistent with our earlier finding about earnings risk and recent evidence that active use of leverage by banks to boost RoE before the crisis was curtailed after the crisis (Pagratis et al. 2020).

Opacity is found to have a negative short-run effect on PB according to Models 1 that is driven by the period during and after crisis (Model 2). This negative effect is consistent with evidence by Jones et al. (2013) that higher opacity leads to lower bank valuations. But the long-run effect of opacity turns out to be positive for the whole sample period in all model specifications. As our opacity measure relates closely with beta (70% correlation), its positive long-run effect on PB may be attributed to the well documented betting-against-beta (BAB) anomaly (Frazzini and Pedersen, 2014). Specifically, contrary to the basic premise of CAPM, high-beta (high-opacity) stocks have lower risk-adjusted returns (higher PB) than low-beta stocks because leverage constraints force long-term investors to overweight higher beta assets in their portfolios to suit their risk profiles.

Bank size has a negative effect on PB over the whole sample period (Models 1 and 2) indicating diseconomies of scale or scope, in line with evidence for systemically important banks by Bogdanova et al. (2018) and Demirguc-Kunt and Huizinga (2013). According to Model 3 such valuation discount is reduced in the short-run by corruption given the positive and significant interactions (0.226 for BC; 0.300 for DAC). But corruption seems to increase the valuation discount due to size in the long-run, especially during and after crisis, given the negative interaction effect (-0.045 for DAC).

GDP growth has a positive effect on PB that is primarily driven by the period before crisis, in line with Demirguc-Kunt and Huizinga (2013) and Jones et al. (2013). For the period during and after crisis, the market appears to be less rewarding for GDP performance when perceptions of public sector corruption are high, given the negative interaction effect both for the short-run (-0.003 for DAC) and the long-run (-0.004 for DAC). This becomes evident in Section 4.3 where we discuss marginal and economic effects.

4.2. Speed of adjustment

In Models 1 and 2 the error-correction parameter φ is found in the range $(-2, 0)$ indicating model stability. In Model 1, the speed of adjustment $-\varphi$ is 0.147 for the whole sample period (1998:Q1-2018:Q1). Model 2 indicates a speed of adjustment of 0.120 before crisis (1998:Q1-2007:Q2) implying that, conditional on characteristics, convergence to equilibrium is expected in 37 quarters. The speed of adjustment increases to 0.192 during and after crisis (2007:Q3-2018:Q1), with full convergence expected in almost 22 quarters.[13]

Model 3 confirms that the speed of adjustment is lower before crisis. In fact, the direct effect of the error-correction parameter is negative and smaller in absolute terms before the crisis (-0.040) than during and after the crisis (-0.195). Moreover, the indirect (interaction) effect is higher (and positive) before crisis (0.078) than during and after crisis (0.033). Keeping other things equal, the absolute combined effect is therefore lower on average before crisis. In addition, corruption appears to slow down the adjustment to equilibrium as indicated by the positive sign of the interaction effect with the error-correction term.

As discussed next, we document a decoupling of PB from fundamentals for high corruption scores before the crisis. In particular, for high levels of corruption, we show that the combined error-correction parameter in Model 3 is outside the range $(-2, 0)$, thus the equilibrium relationship breaks down. In all other cases, Model 3 implies a stable co-integrating relationship, in line with Models 1 and 2.

4.3. Marginal and economic effects

With the estimated Model 3 in hand (see Table 4) we are able to calculate corruption-related marginal effects of fundamentals on PB. We perform this exercise by combining the direct effect of each fundamental variable

[13] It easily follows from Models 1 and 2 that for given set of initial conditions and following t iterations, distance from equilibrium is given by $1 - (1 + \varphi)^t$.

with its interaction effect with corruption. Marginal effects are obtained per corruption quartile to visualize any corruption-dependence.

For ease of exposition, consider the estimated Model 3 focusing on each of the two periods separately: "before crisis" (BC=1 and DAC=0), and "during and after crisis" (BC=0 and DAC=1).

$$\Delta\widehat{PB}_{i,t} = \hat{\varphi}\cdot PB_{i,t-1} + \hat{\varphi}_1\cdot GC_{i,t}\cdot PB_{i,t-1} + \hat{\alpha}\cdot GC_{i,t-1} + \widehat{\boldsymbol{\beta}}\cdot \boldsymbol{X}_{i,t-1} + \widehat{\boldsymbol{\gamma}}\cdot GC_{i,t}\cdot \boldsymbol{X}_{i,t-1} + \hat{\alpha}_0\cdot \Delta GC_{i,t} + \widehat{\boldsymbol{\beta}}_0\cdot \Delta\boldsymbol{X}_{i,t} + \widehat{\boldsymbol{\gamma}}_0\cdot GC_{i,t}\cdot \Delta\boldsymbol{X}_{i,t} + \hat{c} + \hat{c}_i + \hat{c}_t \quad (9)$$

For each corruption quartile $j = 1,2,3,4$ the short-run marginal effects of characteristics $\boldsymbol{X}$ equal the sum of the estimated effects $\widehat{\boldsymbol{\beta}}_0$ of current first differences plus the interaction effects $\widehat{\boldsymbol{\gamma}}_{\mathbf{0}}\cdot\overline{GC_j}$ calculated at the mean corruption level $\overline{GC_j}$ in that quartile: $\widehat{\boldsymbol{\beta}}_0 + \widehat{\boldsymbol{\gamma}}_{\mathbf{0}}\cdot\overline{GC_j}$. The long-run marginal effects equal the sum of estimated effects $\widehat{\boldsymbol{\beta}}$ of lagged levels plus the interaction effects $\widehat{\boldsymbol{\gamma}}\cdot\overline{GC_j}$ at the mean corruption level in the respective quartile, divided by the sum of estimated speed of adjustment $-\hat{\varphi}$ plus its interaction effect $-\hat{\varphi}\cdot\overline{GC_j}$ at mean corruption: $-\left[\widehat{\boldsymbol{\beta}} + \widehat{\boldsymbol{\gamma}}\cdot\overline{GC_j}\right]/\left[\hat{\varphi} + \hat{\varphi}_1\cdot\overline{GC_j}\right]$.

Estimated marginal effects are presented in Table 5.A for the periods before crisis and in Table 5.B for the period during and after crisis. To help assess the economic significance of fundamentals on PB we also report their respective economic effects in each corruption quartile. These are defined as the marginal effects multiplied by the respective standard deviations of fundamentals in the quartile.

[Table 5.A about here]

[Table 5.B about here]

As a first observation, convergence to equilibrium slows down as corruption increases. This means that, in jurisdictions with high perceived corruption, PB ratios spend more time away from fundamental levels. Before the crisis, the speed of adjustment $-\varphi$ is estimated at 22%, 15% and 10% in the 1st, 2nd and 3rd corruption quartile, respectively, as shown in Table 5.A. That is, conditional on $\boldsymbol{X}$, more than 99% convergence to equilibrium is expected to be attained in 19, 29 and 45 quarters. The speed of adjustment during and after crisis is 26%, 24%, 22% and 18% in the 1st, 2nd, 3rd and 4th corruption quartiles, implying more than 99% convergence in 16, 17, 19 and 24 quarters, respectively.

Notice there is a decoupling of PB from fundamentals before crisis in the 4th corruption quartile given that the estimated error-correction term is statistically insignificant. As there is no equilibrium relationship in that case, we abstract from discussing long-run effects in the 4th corruption quartile before crisis.

The marginal effect of DPR and its statistical significance decreases with corruption, both in the short-run and the long-run. This result holds for the whole sample period (Tables 5.A and 5.B) suggesting a declining pass-through of DPR to PB as corruption increases.

Expected growth has an insignificant marginal effect on PB before crisis. But during and after crisis it has a positive marginal effect in the 1st corruption quartile, especially in the long-run. In other words, the market seems to reward expected growth in net income as long as the bank operates in a low corruption regime. But the marginal effect of expected growth turns negative in higher corruption quartiles (3 and 4). A possible explanation is that the higher the corruption, the more the market may associate greater expected growth with excessive risk-taking.

Similarly, the marginal effect of earnings risk (sigma RoE) becomes more negative (and significant) as corruption increases. This is particularly evident during and after crisis, confirming that market sensitivity to earnings risk increases with corruption. Moreover, earnings risk prevails as a risk measure in our specification when corruption interactions are taken into account. Cost of equity has an insignificant marginal effect before crisis, which only becomes significant (and negative) during and after crisis in the short-run and for high levels of corruption (quartile 4).

Leverage has a significant (positive) marginal effect on PB in all corruption quartiles over the whole sample period. But such a valuation premium weakens during and after crisis, possibly as a result of market re-appraisal of the effect of leverage on RoE riskiness, in line with our earlier finding about earnings risk. In addition, a weaker valuation premium due to higher leverage may be associated with a significant deleveraging of the banking system in the aftermath of the crisis as a result of large scale recapitalizations and tighter capital regulations, especially for systemically important banks.

Opacity has a significant and negative marginal effect on PB in the short-run during and after crisis, implying that higher opacity is associated with lower bank valuations. In other words, the market appears to reward transparency. But as corruption increases, the positive valuation effect of transparency seems to fade out and become insignificant in quartile 4.

Bank size implies a valuation discount that is mitigated by corruption in the short-run and exacerbated in the long-run. In fact, larger banks may be better placed to benefit from corruption though lobbying and cronyism that limit public scrutiny or formal procurement processes. Therefore, corruption may mitigate diseconomies of scale or scope in the short-run. But in the long-run, it could exacerbate inefficiencies, increasing the size-related valuation discount.

GDP growth implies a bank valuation premium, both in the short-run and the long-run. But as public sector corruption deteriorates, the valuation premium associated with GDP growth decreases in the period during and after crisis and becomes insignificant in high corruption regimes (quantile 4). This is tantamount to GDP performance weighing less in bank valuations as perceptions of public sector corruption deteriorate.

Summarizing, the results show that corruption enters the transmission channels of characteristics to PB both through negative and positive indirect effects, i.e. negative and positive cross derivatives of PB with respect to corruption and characteristics ($\partial^2 PB/\partial X \partial GC$).

Especially for the long-run relationship, marginal effects across corruption quartiles in Tables 5.A and 5.B reveal that the indirect effect of corruption on PB is negative ($\partial^2 PB/\partial X \partial GC < 0$) with respect to DPR

(BC, DAC), expected growth in net income (DAC), earnings risk (DAC), opacity (DAC), size (BC, DAC), and GDP growth (DAC). The indirect effect of corruption is positive ($\partial^2 PB/\partial X \partial GC > 0$) with respect to leverage (BC, DAC), opacity (BC), and GDP growth (BC). In terms of economic effect, the most important factors turn out to be DPR, leverage, opacity, and size.

What is the overall effect of public sector corruption on G-SIBs valuation? To answer this question we conduct a counterfactual experiment considering hypothetical scenarios where banks migrate from the corruption regimes of their domicile to higher or lower corruption quartiles, keeping other characteristics constant. The overall effect of corruption on PB is then calculated for each migration as the average difference between long-run PB values in the destination and originating quartiles using the panel-ARDL model of equation (9). We also present transition dynamics to visualise the path to equilibrium.

5. Overall effect of corruption

Differences across countries in public-sector corruption may lead to distortions of level playing field with respect to bank valuations. Higher corruption may imply a hidden subsidy that boosts PB conditional on bank characteristics ("grease in the wheels", for example, Borisov, 2016; Gropper et al., 2013; Collins, 2009; Faccio, 2006; Fisman 2001; Brass et al., 1998; Oliver 1997). On the other hand, corruption could erode bank charter value and lead to lower PB ("sand in the wheels", for example, Brown et al. 2021; Dass et al. 2016; Djakov et al., 2008; Dyck and Zingales, 2004; Shleifer and Vishny, 1993).

To evaluate any distortionary effect of corruption on PB we consider hypothetical scenarios where each bank migrates from the domicile regime to a higher or lower corruption quartile, keeping all other characteristics constant. The distortionary effect of corruption is then measured by the (pooled) average difference in long-run (fundamental) PB between the originating and destination quartile.

More specifically, let $\widetilde{PB}_{i,t,q}^{LR}$ be the long-run PB of bank i with characteristics $\boldsymbol{X}_{i,t}$ at time t, calculated at the average corruption level $\overline{GC}_q$ at destination quartile q using equation (9). Let also $\widehat{PB}_{i,t}^{LR}$ be the in-sample point estimate of the long-run PB at originating quartile. We measure the distortionary effect of corruption by the pooled average difference $\left(\widetilde{PB}_{i,t,q}^{LR} - \widehat{PB}_{i,t}^{LR}\right)$.

Given that $\left|\hat{\varphi} + 1 + \hat{\varphi}_1 \cdot \overline{GC}_q\right| < 1$ and $\left|\hat{\varphi} + 1 + \hat{\varphi}_1 \cdot GC_{i,t}\right| < 1$, the log-run values $\widetilde{PB}_{i,t,q}^{LR}$, $\widehat{PB}_{i,t}^{LR}$ obtain from equation (9) by forward substitution for corruption level $\overline{GC}_q$, $GC_{i,t}$, respectively.

$$\widetilde{PB}_{i,t,q}^{LR} = -\frac{\hat{\alpha} \cdot \overline{GC}_j + (\hat{\boldsymbol{\beta}} + \hat{\boldsymbol{\gamma}} \cdot \overline{GC}_j) \cdot \boldsymbol{X}_{i,t} + \hat{c}_{i,t}}{\hat{\varphi} + \hat{\varphi}_1 \cdot \overline{GC}_q} \tag{10}$$

$$\widehat{PB}_{i,t}^{LR} = -\frac{\hat{\alpha} \cdot GC_{i,t} + (\hat{\boldsymbol{\beta}} + \hat{\boldsymbol{\gamma}} \cdot GC_{i,t}) \cdot \boldsymbol{X}_{i,t} + \hat{c}_{i,t}}{\hat{\varphi} + \hat{\varphi}_1 \cdot GC_{i,t}} \tag{11}$$

where, $\hat{c}_{i,t} = \hat{c} + \hat{c}_i + \hat{c}_t$ is the sum of estimated constant $\hat{c}$, bank effect $\hat{c}_i$, and time effect $\hat{c}_t$.

In fact, conditional on characteristics $\boldsymbol{X}_{i,t}$ and for corruption levels $\overline{GC}_q$ and $GC_{i,t}$, forward substitution of equation (9) by w periods yields the best guess of $PB_{i,t+w}$ as given by equations (12) and (13), respectively.

$$\widetilde{PB}_{i,t+w,q} = PB_{i,t} \cdot \left(\hat{\varphi} + 1 + \hat{\varphi}_1 \cdot \overline{GC}_q\right)^w + \left[\hat{\alpha} \cdot \overline{GC}_q + \left(\hat{\boldsymbol{\beta}} + \hat{\boldsymbol{\gamma}} \cdot \overline{GC}_q\right) \cdot \boldsymbol{X}_{i,t} + \hat{c}_{i,t}\right] \cdot \sum_{m=1}^{w} \left(\hat{\varphi} + 1 + \hat{\varphi}_1 \cdot \overline{GC}_q\right)^{m-1} \quad (12)$$

$$\widehat{PB}_{i,t+w} = PB_{i,t} \cdot \left(\hat{\varphi} + 1 + \hat{\varphi}_1 \cdot GC_{i,t}\right)^w + \left[\hat{\alpha} \cdot GC_{i,t} + \left(\hat{\boldsymbol{\beta}} + \hat{\boldsymbol{\gamma}} \cdot GC_{i,t}\right) \cdot \boldsymbol{X}_{i,t} + \hat{c}_{i,t}\right] \cdot \sum_{m=1}^{w} \left(\hat{\varphi} + 1 + \hat{\varphi}_1 \cdot GC_{i,t}\right)^{m-1} \quad (13)$$

In the limit for $w \to \infty$, equations (12) and (13) yield the long-run values of equations (10) and (11). By plotting the pooled average difference $\left(\widetilde{PB}_{i,t+w,q} - \widehat{PB}_{i,t+w}\right)$ for $w = 1,2,\ldots\infty$ we visualize the transition dynamics of corruption-related distortions to PB in the path to equilibrium, as shown in Figure 1.

[Figure 1 about here]

Table 6 shows pooled average differences in long-run values $\left(\widetilde{PB}_{i,t,q}^{LR} - \widehat{PB}_{i,t}^{LR}\right)$ under hypothetical departures from domicile regimes (first column) to different corruption quartiles (first row), keeping other characteristics constant. Panel A relates to the period "before crisis" and Panel B to "during and after crisis".

[Table 6 about here]

In the "before crisis" period we document a positive overall effect of corruption on fundamental PB.[14] We interpret this as evidence of a hidden PB subsidy associated with higher levels of public sector corruption. Specifically, hypothetical migrations from corruption quartile 1 to 2 or 3 lead to an average increase in fundamental PB by 0.220 or 0.582, respectively. Similarly, moving from corruption quartile 2 to 3 leads to an average increase of fundamental PB by 0.234. On the other hand, migrating from quartile 2 to 1 reduces fundamental PB by -0.183 on average, and migrations from quartile 3 to 2 and 1 result in an average reduction of -0.248 and -0.354, respectively. As there is no convergence to equilibrium for high levels of corruption before crisis, we perform no hypothetical migration (departure) to (from) corruption quartile 4.

It is also significant that "during and after crisis" the overall effect of public sector corruption on fundamental PB becomes negative, i.e. the implicit subsidy documented "before crisis" appears to reverse.[15] That is, hypothetical migrations from corruption quartile 1 to 2, 3 and 4 lead to an average decrease in fundamental PB by -0.070, -0.145 and -0.401, respectively. Similarly, moving from corruption quartile 2 to 3 and 4 leads to an average decrease of fundamental PB by -0.110 and -0.492, while from quartile 3 to 4 by -0.287. On the other hand, a hypothetical migration from quartile 2 to 1 increases fundamental PB by

[14] For the period before crisis, the indirect effect of corruption on long-run PB is positive ($\partial^2 PB/\partial X \partial GC > 0$) with respect to leverage, opacity, and GDP growth (see Table 5.A). In addition, leverage turns out to be one of the factors with the largest economic effect on long-run PB across corruption quartiles, along with DPR and size. Given that DPR and size have a negative indirect effect on PB with respect to corruption ($\partial^2 PB/\partial X \partial GC < 0$) it follows that the positive overall effect of corruption before crisis is primarily attained through the leverage channel.

[15] For the period during and after crisis, the indirect effect of corruption on PB is negative ($\partial^2 PB/\partial X \partial GC < 0$) with respect to DPR, expected growth, earnings risk, opacity, size, and GDP growth (see Table 5.B). In addition, DPR and size are two of the three most important factors in terms of economic effect across corruption quartiles. Given that the third most important factor (leverage) has a positive indirect effect on PB ($\partial^2 PB/\partial X \partial GC > 0$) it follows that the negative overall effect of corruption during and after crisis occurs mainly through the DPR and size channels.

0.123 on average, while from quartile 3 to 2 and 1 by 0.054 and 0.138, respectively. Finally, moving from quartile 4 to 3, 2 and 1 increases fundamental PB on average by 0.190, 0.241 and 0.296, respectively.

The reversal of the overall effect of corruption on fundamental PB – from positive before crisis to negative during and after crisis – is primarily driven by the marked weakening of the leverage channel through which corruption plays out in bank valuations. Tables 5.A. and 5.B show that leverage experiences the largest drop in economic effect between the two periods (BC and DAC) and such a drop gets larger the higher the corruption level, i.e. a drop in the economic effect of leverage by -0.229, -0.324, and -0.711 in quartiles 1, 2, and 3, respectively (all significant at 1%). In other words, the *difference-in-differences* between the two periods as corruption increases is -0.095 between quartiles 1 and 2 (significant at 5%), -0.387 between quartiles 2 and 3 (significant at 1%), and -0.482 between quartiles 1 and 3 (significant at 1%). A possible explanation of such a weakening in the leverage channel in the aftermath of the crisis is the large scale recapitalization of systemically important banks, along with policy response – notably Basel III – that had a lasting deleveraging effect because of increased emphasis on quantity and quality of bank capital buffers.

On the other hand, DPR and size – the most important factors along with leverage – do not add to the reversal of the overall effect of corruption on fundamental PB, from positive BC to negative DAC. Notwithstanding the economic effect of DPR increasing after the crisis, its differential effect between the two periods (remains statistically unaltered across corruption quartiles (zero difference-in-differences). In addition, the negative economic effect of size is mitigated after the crisis, and even more so for higher levels of corruption. In fact, the differential effect of size between the two periods (BC and DAC) increases by 0.161 between quartiles 1 and 2 (significant at 1%), 0.238 between quartiles 2 and 3 (significant at 5%), and 0.399 between quartiles 1 and 3 (significant at 1%).

6. Conclusions

Bank capital buffers have improved substantially after the global financial crisis, but market indicators of bank solvency – notably the PB ratio – have adjusted markedly lower. This led to calls for capital neutral rules for banks going forward, renewing focus on rules implementation and a level playing field for cost of capital. PB could be affected by the quality of public institutions, supervisory conduct and, in particular, corruption entrenchment in the official sector. Public sector corruption could have both a positive and a negative effect on PB. On the one hand, it could offer banks more lever to feed into policy preferences and an opportunity to sustain competitive advantages. In that sense it could enhance shareholder value through supervisory forbearance, reduced policy uncertainty and stifled competition ("grease in the wheels"). On the other hand, connections with corrupt officials could facilitate investor expropriation by means of self-dealing by insiders. In that sense, public sector corruption could undermine bank corporate governance, distort pricing and the allocation of financial resources, therefore reducing PB ("sand in the wheels").

In this paper we explore the valuation dynamics of G-SIBs and possible ways that they relate to public sector corruption. Corruption enters the transmission channel of characteristics to PB through both negative and positive indirect effects. Hypothetical migrations to higher corruption regimes, keeping other characteristics constant, would increase fundamental PB pre-crisis, suggesting corruption-related distortions of level playing field. The implicit subsidy associated with corruption seems to reverse post-crisis mainly due to substantial weakening of the leverage channel. This could be attributed to large scale recapitalizations, tighter capital standards, and a market re-appraisal of earnings risk stemming from higher leverage post-crisis. In fact, market sensitivity to earnings risk increases with corruption and this is particularly evident post-crisis. It is also significant that higher corruption leads to a dwindling pass-through to PB of dividend payout ratios and growth rates in GDP and expected net-income.

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References

Acemoglu, D., Johnson, S., Kermani, A., Kwak, J., and T. Mittone, 2016. The value of connections in turbulent times: Evidence from the United States, *Journal of Financial Economics*, 121(2), 368-391.

Baker, S. R., Bloom, N., and S. J. Davis, 2016. Measuring economic policy uncertainty, *Quarterly Journal of Economics*, 131(4), 1593-1636.

Bertsatos, G., Sakellaris, P., and M. Tsionas, 2017. Did the financial crisis affect the market valuation of large systemic U.S. banks?, *Journal of Financial Stability*, 32(3), 115-123.

Bertsatos, G. and P. Sakellaris, 2016. A dynamic model of bank valuation, *Economics Letters*, 2016, 145, 15-18.

Bertsatos, G., Sakellaris, P., and M. Tsionas, 2022a. Extensions of the Pesaran, Shin and Smith (2001) Bounds Testing Procedure, *Empirical Economics*, 62, 605-634..

Bertsatos, G., Sakellaris, P., and M. Tsionas, 2022b. A panel bounds testing procedure, Athens University of Economics and Business, *mimeo*.

Bogdanova, B., Fender, I., and E. Takats, 2018. The ABCs of bank PBRs, *BIS Quarterly Review*, March.

Borisov, A., Goldman, E., and N. Gupta, 2016. The Corporate Value of (Corrupt) Lobbying, *Review of Financial Studies*, 29(4), 1039–1071.

Bostandzic, D., Irresberger, F., Juelsrud R.E., and G.N.F Weiss, 2021. Do Capital Requirements Make Banks Safer? Evidence From a Quasi-Natural Experiment , *Journal of Financial and Quantitative Analysis*, forthcoming.

Brass, D. J., D. Butterfield, D., and B. C. Skaggs, 1998. Relationships and unethical behavior: A social network perspective, Academy of Management Review, 23(1), 14–32.

Brown, N. C., Smith, J. D., White, R. M., and C. J. Zutter, 2021. Political corruption and firm value in the U.S.: Do rents and monitoring matter?, *Journal of Business Ethics*, 168, 335-351.

Calomiris, C. and D. Nissim, 2014. Crisis-related shifts in the market valuation of banking activities, *Journal of Financial Intermediation*, 23(3), 400-435.

Cho, J.S., Kim, T., and Y. Shin, 2015. Quantile cointegration in the autoregressive distributed-lag modeling framework, *Journal of Econometrics*, 188(1), 281-300.

Choi, I., 2001. Unit root tests for panel data. *Journal of International Money and Finance*, 20(1), 249-272.

Christopoulos, D., McAdam, P., and E. Tzavalis, 2021. Dealing with endogeneity in threshold models using copulas, *Journal of Business & Economic Statistics*, 39(1), 166-178.

Claessens, S., Feijen, E., and L. Laeven, 2008. Political connections and preferential access to finance: The role of campaign contributions, *Journal of Financial Economics*, 88(3), 554-580.

Collins, J. D., Uhlenbruck, K., and P. Rodriguez, 2009. Why firms engage in corruption: A top management perspective, *Journal of Business Ethics*, 87(1), 89-108.

Damodaran, A., 2012. Investment valuation: Tools and techniques for determining the value of any asset, 3rd edition. Hoboken, New Jersey: John Wiley & Sons, Inc., p. 992.

Dass, N., Nanda, V., and S. C. Xiao, 2016. Public corruption in the United States: Implications for local firms, *Review of Corporate Finance Studies*, 5(1), 102-138.

Demirguc-Kunt, A. and H. Huizinga, 2013. Are banks too big to fail or too big to save? International evidence from equity prices and CDS spreads, *Journal of Banking and Finance*, 37(3), 875-894.

Dinc, S., 2005. Politicians and banks: political influences on government-owned banks in emerging markets. Journal of Financial Economics 77(2), 453–479.

Djankov, S., La Porta, R., Lopez-de-Silanes, F., and A. Shleifer, 2008. The law and economics of self-dealing, *Journal of Financial Economics*, 88(3), 430-465.

Dyck, A. and L. Zingales, 2004. Private benefits of control: An international comparison, *Journal of Finance*, 59(2), 537–600.

Faccio, M., 2006. Politically connected firms, *American Economic Review*, 96(1), 369-386.

Fisman, R., 2001. Estimating the value of political connections, *American Economic Review*, 91(4), 1095-1102.

Fisman, R. and E. Miguel, 2007. Corruption, norms and legal enforcement: Evidence from diplomatic parking tickets, *Journal of Political Economy*, 115(6), 1020–1049.

Frazzini, A. and L.H. Pedersen, 2014. Betting against beta, *Journal of Financial Economics* 111(1), 1-25.

Gropper, D. M., Jahera, J. S., and J. C. Park, 2013. Does it help to have friends in high places? Bank stock performance and congressional committee chairmanships, *Journal of Banking and Finance*, 37(6), 1986-1999.

Grossman, E. and C. Woll, 2014. Saving the Banks: The Political Economy of Bailouts, *Comparative Political Studies*, 47(4), 574-600.

Haselmann, R., Schoenherr, D., and V. Vig, 2018. Rent seeking in elite networks, *Journal of Political Economy*, 126(4), 1638-1690.

Houston, J. F., Jiang, L., Lin, C., A. Yue Ma, 2014. Political connections and the cost of bank loans, *Journal of Accounting Research*, 52(1), 193-243.

Im, K. S., Pesaran, M. H., and Y. Shin, 2003. Testing for unit roots in heterogeneous panels, *Journal of Econometrics*, 115(1), 53-74.

Jones, J. S., Lee, W. Y., and T. J. Yeager, 2013. Valuation and systemic risk consequences of bank opacity, *Journal of Banking and Finance*, 37(3), 693-706.

Khwaja, A. I. and A. Mian, 2005. Do lenders favor politically connected firms? Rent provision in an emerging financial market, *Quarterly Journal of Economics*, 120(4), 1371-1411.

La Porta, R., Lopez-de-Silanes, F., and A. Shleifer, 2002. Government ownership of banks, *Journal of Finance* 57(1), 256–301.

Laeven, L., 2001. Insider lending and bank ownership: The case of Russia, *Journal of Comparative Economics*, 29(2), 2001, 207-229.

Maddala, G. S. and S. Wu, 1999. A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test, *Oxford Bulletin of Economics and Statistics*, 61(1), 631-652.

Nickell, S., 1981. Biases in dynamic models with fixed effects, *Econometrica*, 49(6), 1417-1426.

Oliver, C., 1997. Sustainable competitive advantage: Combining institutional and resource-based views, *Strategic Management Journal*, 18(9), 697–713.

Pagratis, S., Louri, E. and E. Karakatsani, 2020. Are banks using leverage to target return on equity? Evidence from the US and the EU, *Oxford Economic Papers*, 72, 863–892.

Park, J., 2012. Corruption, soundness of the banking sector, and economic growth: A cross-country study, *Journal of International Money and Finance*, 31(5), 907-929.

Pesaran, M.H. and Y. Shin, 1999. An autoregressive distributed lag modelling approach to cointegration analysis, in: Strom, S. (ed.). Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium, Cambridge University Press, Cambridge, 371-413.

Pesaran, M. H., Shin, Y., and R. J. Smith, 2001. Bounds Testing Approaches to the Analysis of Level Relationships, *Journal of Applied Econometrics*, 16(1), 289-326.

Rose-Ackerman, S., 1975. The economics of corruption, *Journal of Public Economics*, 4(2), 187–203.

Sapienza, P., 2004. The Effects of Government Ownership on Bank Lending, *Journal of Financial Economics*, 72(2), 357–84.

Sarin, N. and L. Summers, 2016. Understanding Bank Risk through Market Measures, *Brookings Papers on Economic Activity*, Fall, 57-109.

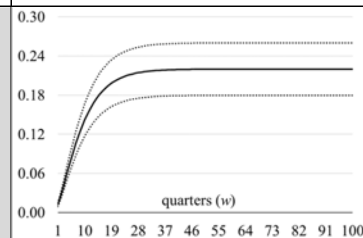
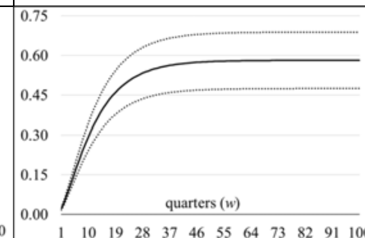
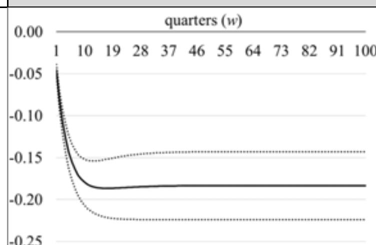
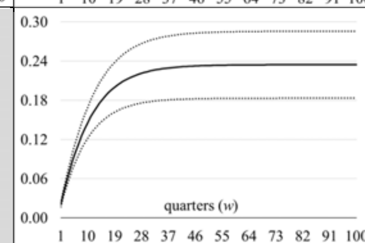
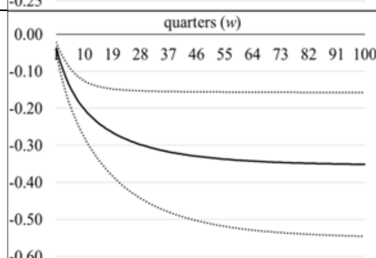
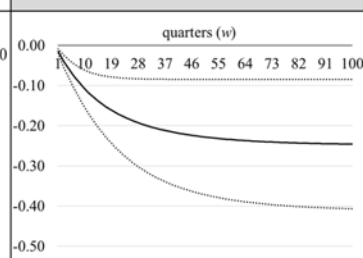
Shin, Y., Yu, B., and M. J. Greenwood-Nimmo, 2014. Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework, in: Horrace, William, C., Sickles, Robin, C. (Eds.), Festschrift in Honor of Peter Schmidt. Springer Science & Business Media, New York.

Shleifer, A., and R. Vishny, 1993. Corruption. *Quarterly Journal of Economics,* 108(3), 599–617.

Uslaner, E. M. and B. Rothstein, 2016. The historical roots of corruption: State building, economic inequality, and mass education, *Comparative Politics*, 48(2), 227-248.

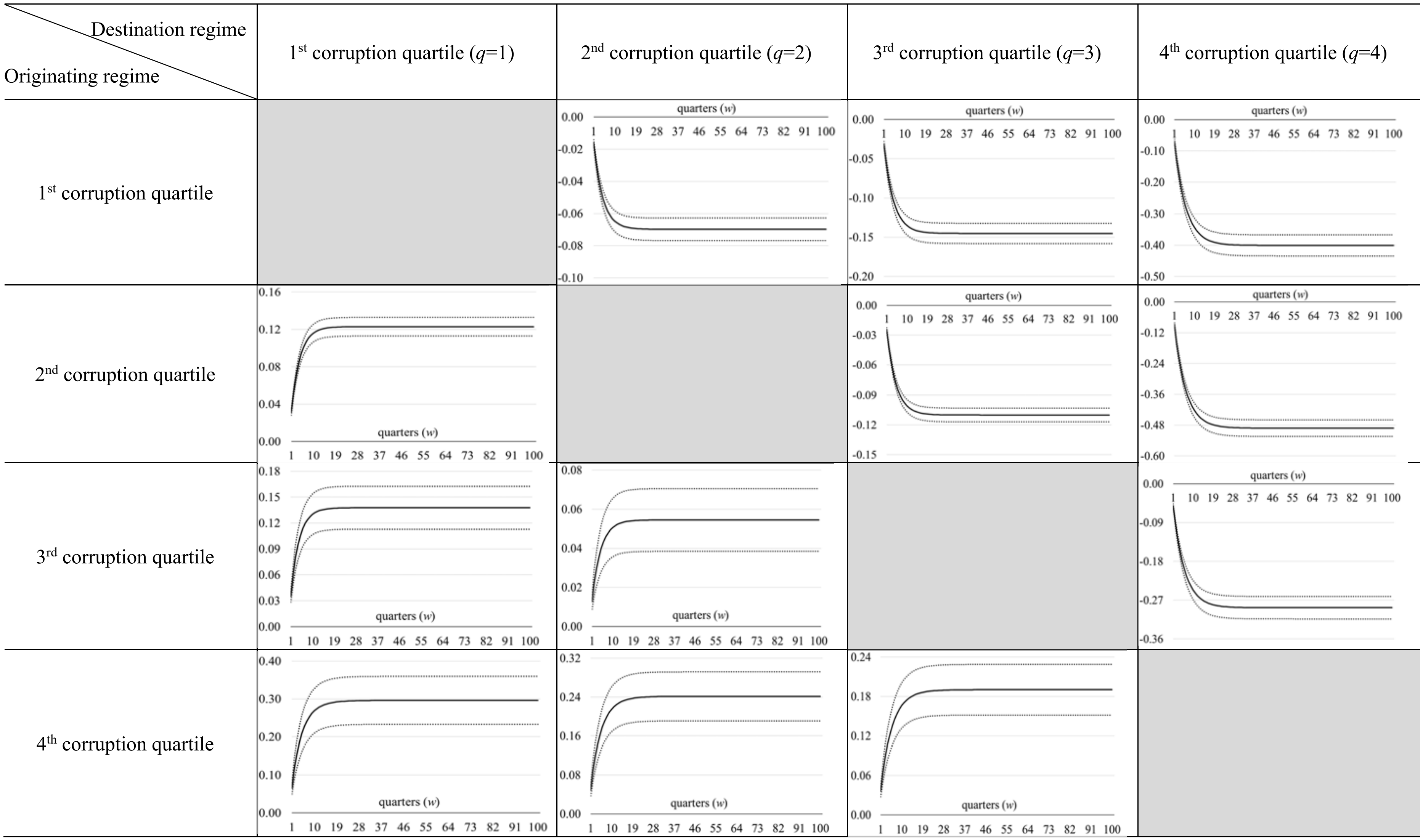
Figures

FIGURE 1.A Corruption-related distortions of G-SIBs fundamental valuation in the path to equilibrium, before the crisis (1998:Q1-2007:Q2)

<table>
<tr><th>Destination regime / Originating regime</th><th>1st corruption quartile (q=1)</th><th>2nd corruption quartile (q=2)</th><th>3rd corruption quartile (q=3)</th><th>4th corruption quartile (q=4)</th></tr>
<tr><td>1st corruption quartile</td><td></td><td>
</td><td>
</td><td>NC</td></tr>
<tr><td>2nd corruption quartile</td><td>
</td><td></td><td>
</td><td>NC</td></tr>
<tr><td>3rd corruption quartile</td><td>
</td><td>
</td><td></td><td>NC</td></tr>
<tr><td>4th corruption quartile</td><td>NC</td><td>NC</td><td>NC</td><td></td></tr>
</table>

This figure shows transition dynamics of corruption-related distortions to fundamental PB because of public-sector corruption before the crisis (1998:Q1-2007:Q2). For each bank i at time t, let $\widetilde{PB}_{i,t+w,q}$ the best guess of w-quarters ahead PB conditional on characteristics $\boldsymbol{X}_{i,t}$ and average corruption level at destination quartile q, as of equation (12). Let also $\widehat{PB}_{i,t+w}$ the best guess of w-quarters ahead PB conditional on characteristics $\boldsymbol{X}_{i,t}$ and corruption level in the country of domicile, as of equation (13). Transition dynamics of corruption-related distortions to fundamental PB are depicted by the pooled average difference $\widetilde{PB}_{i,t+w,q} - \widehat{PB}_{i,t+w}$ for w=1,2… Two-standard-error confidence intervals are shown by dotted lines. *NC* denotes no co-integration.

FIGURE 1.B Corruption-related distortions of G-SIBs fundamental valuation in the path to equilibrium, during and after crisis (2007:Q3-2018:Q1)



This figure shows transition dynamics of corruption-related distortions to fundamental PB because of public-sector corruption during and after crisis (2007:Q3-2018:Q1). For each bank i at time t, let $\widetilde{PB}_{i,t+w,q}$ the best guess of w-quarters ahead PB conditional on characteristics $\boldsymbol{X}_{i,t}$ and average corruption level at destination quartile q, as of equation (12). Let also $\widehat{PB}_{i,t+w}$ the best guess of w-quarters ahead PB conditional on characteristics $\boldsymbol{X}_{i,t}$ and corruption level in the country of domicile, as of equation (13). Transition dynamics of corruption-related distortions to fundamental PB are depicted by the pooled average difference $\widetilde{PB}_{i,t+w,q} - \widehat{PB}_{i,t+w}$ for w=1,2… Two-standard-error confidence intervals are shown by dotted lines. *NC* denotes no co-integration.

Tables

TABLE 1 Global Systemically Important Banks (G-SIBs) according to Basel Committee on Banking Supervision (BCBS), for the period 1998:Q1-2018:Q1

Country	**G-SIBs**	**Unlisted G-SIBs**	**Listed G-SIBS with less than 20 obs.**	**Listed G-SIBs used in estimation**
Australia	ANZ, Commonwealth, National Australia Bank, Westpac			ANZ, Commonwealth, National Australia Bank, Westpac
Belgium	KBC			KBC, Dexia
Brazil	Banco Bradesco, Banco do Brasil, Itau Unibanco			Banco Bradesco, Banco do Brasil, Itau Unibanco
Canada	Bank of Montreal, Bank of Nova Scotia, Canadian Imperial Bank of Commerce, Royal Bank of Canada, Toronto Dominion			Bank of Montreal, Bank of Nova Scotia, Canadian Imperial Bank of Commerce, Royal Bank of Canada, Toronto Dominion
China	Agricultural Bank of China, Bank of Beijing, Bank of China, Bank of Communications, Bank of Jiangsu, China Construction Bank, China Everbright, China Guanfa, China Merchants, China Minsheng, China Zheshang Bank, CITIC, Hua Xia, Industrial and Commercial Bank of China, Industrial Bank Co, Oversea Chinese Bank Corporation, Ping An, Shangai Pudong	China Guanfa	Agricultural Bank of China, Bank of Jiangsu, China Everbright, China Zheshang Bank, Hua Xia, Ping An	Bank of Beijing, Bank of China, Bank of Communications, China Construction Bank, China Merchants, China Minsheng, CITIC, Industrial and Commercial Bank of China, Industrial Bank Co, Oversea Chinese Bank Corporation, Shangai Pudong
Denmark	Danske Bank, Nykredit Realkredit	Nykredit Realkredit		Danske Bank
France	Banque Populaire CdE, BNP Paribas, Credit Agricole, Credit Mutuel, Postale, Societe Generale	Banque Populaire CdE, Credit Mutuel, Postale		BNP Paribas, Credit Agricole, Societe Generale
Germany	Bayern LB, Commerzbank, Deutsche Bank, DZ Bank, Helaba, LBBW, NORD LB	Bayern LB, DZ Bank, Helaba, LBBW, NORD LB		Commerzbank, Deutsche Bank
India	State Bank of India			State Bank of India
Italy	Intensa, Monte dei Paschi di Siena, Unicredit Group			Intensa, Monte dei Paschi di Siena, Unicredit Group
Japan	Mitsubishi UFJ FG, Mizuho FG, Nomura, Norinchukin, Sumitomo Mitsui FG, Sumitomo Mitsui Trust	Norinchukin		Mitsubishi UFJ FG, Mizuho FG, Nomura, Sumitomo Mitsui FG, Sumitomo Mitsui Trust
Netherlands	ABN Amro, ING Group, Rabobank	Rabobank	ABN Amro	ING Group
Norway	DNB Bank			DNB Bank
Russia	PAO Sberbank			PAO Sberbank
Singapore	DBS Bank, United Overseas Bank			DBS Bank, United Overseas Bank
South Korea	Hana FG, Industrial Bank of Korea, KDB, Kookmin, Nonghyup, Shinhan, Wooribank	KDB, Nonghyup	Kookmin	Hana FG, Industrial Bank of Korea, Shinhan, Wooribank
Spain	BBVA, Bankia, Caixabank, Sabadell, Santader		Bankia	BBVA, Caixabank, Sabadell, Santader
Sweden	Handelsbanken, Nordea, Skandinaviska Enskilda Banken, Swedbank			Handelsbanken, Nordea, Skandinaviska Enskilda Banken, Swedbank
Switzerland	Credit Suisse, UBS			Credit Suisse, UBS
UK	Barclays, HSBC, Lloyds Banking Group, Nationwide Building Society, Royal Bank of Scotland, Standard Chartered	Nationwide Building Society		Barclays, HSBC, Lloyds Banking Group, Royal Bank of Scotland, Standard Chartered
USA	Bank of America, BB&T, Capital One, Charles Schwab, Citigroup, JPMorgan Chase, Morgan Stanley, State Street, SunTrust Bank, The Bank of New York Mellon, The Goldman Sachs Group, The PNC Financial Services Group, U.S. Bancorp, Wells Fargo		Charles Schwab	Bank of America, BB&T, Capital One, Citigroup, JPMorgan Chase, Morgan Stanley, State Street, SunTrust Bank, The Bank of New York Mellon, The Goldman Sachs Group, The PNC Financial Services Group, U.S. Bancorp, Wells Fargo

This table shows banks by country classified as G-SIBs according to BCBS (column 2), during the sample period (1998:Q1-2018:Q1). It also shows unlisted G-SIBs (column 3) and those with less than 20 observations (column 4) that we exclude from final sample (column 5). The sample also includes Dexia, which is the only G-SIB according to FSB classification but not according to BCBS.

TABLE 2 Mapping of countries to public sector corruption (GC) quartiles

PANEL A: PERIOD 1998-2007	Below 25th percentile	Between 25th & 50th percentile	Between 50th & 75th percentile	Above 75th percentile
CORRUPTION CUT-OFF	**-1.912**	**-1.059**	**0.020**	**-**
Australia		✓		
Belgium		✓	✓	
Brazil				✓
Canada	✓	✓		
China				✓
Denmark	✓			
France			✓	
Germany		✓	✓	
India				✓
Italy			✓	✓
Japan		✓	✓	
Netherlands	✓	✓		
Norway	✓	✓		
Russia				✓
Singapore	✓			
South Korea			✓	✓
Spain			✓	
Sweden	✓			
Switzerland	✓	✓		
UK		✓		
USA		✓	✓	
Number of countries	**7**	**10**	**8**	**6**
PANEL B: PERIOD 2008-2018	Below 25th percentile	Between 25th & 50th percentile	Between 50th & 75th percentile	Above 75th percentile
CORRUPTION CUT-OFF	**-1.670**	**-1.112**	**-0.139**	**-**
Australia	✓	✓		
Belgium		✓	✓	
Brazil				✓
Canada	✓	✓		
China				✓
Denmark	✓			
France			✓	
Germany		✓		
India				✓
Italy				✓
Japan		✓	✓	
Netherlands	✓	✓		
Norway	✓	✓		
Russia				✓
Singapore	✓	✓		
South Korea			✓	✓
Spain			✓	
Sweden	✓	✓		
Switzerland	✓	✓		
UK		✓	✓	
USA			✓	
Number of countries	**8**	**11**	**7**	**6**

This table maps domicile countries in the final sample to corruption quartiles for the periods 1998-2007 (Panel A) and 2008-2018 (Panel B). Quartile cut-offs are calculated using the corruption variable GC in annual frequency at country level.

TABLE 3 Descriptive statistics per corruption quartile "before crisis" and "during and after crisis", for the sample period 1998:Q1-2018:Q1

PANEL A Period "before crisis - BC" (1998:Q1-2007:Q2)

	Below 25th percentile			Between 25th & 50th percentile			Between 50th & 75th percentile			Above 75th percentile			Total sample		
CORRUPTION CUT-OFF		**-1.912**			**-1.059**			**0.020**			**-**			**-**	
VARIABLE NAME	*Mean*	*Median*	*St.Dev*	*Mean*	*Median*	*St.Dev*	*Mean*	*Median*	*St.Dev*	*Mean*	*Median*	*St.Dev*	*Mean*	*Median*	*St.Dev*
Price to book	1.823	1.782	0.444	2.539	2.398	0.982	2.126	1.820	1.222	1.821	1.549	1.265	2.208	2.014	1.050
Public sector corruption	-2.333	-2.325	0.385	-1407	-1.278	0.318	-0.663	-0.768	0.307	0.585	0.656	0.259	-0.896	-1.059	1.077
Dividend payout ratio (%)	6.351	5.996	2.402	6.961	7.180	3.733	5.162	5.105	2.687	2.758	2.209	2.221	5.897	5.818	3.399
Expected growth (%)	3.802	3.824	1.552	4.197	4.258	2.095	4.410	3.842	4.026	5.059	4.681	3.800	4.270	4.123	2.806
Cost of equity (%)	5.167	4.991	1.417	5.770	5.642	1.251	5.554	5.776	1.841	13.422	11.441	8.312	6.570	5.749	4.208
Sigma RoE (%)	1.043	0.875	0.718	1.413	0.933	1.761	1.889	1.326	2.587	1.694	0.785	2.519	1.471	0.960	1.944
Leverage	22.885	23.650	9.019	19.582	17.422	9.264	27.958	22.258	18.342	18.127	17.932	6.987	21.898	19.349	12.127
Opacity	-2.517	-2.333	1.195	-2.329	-2.152	1.112	-2.863	-2.612	1.232	-3.970	-3.204	1.887	-2.693	-2.420	1.384
Size	25.953	25.907	0.822	26.300	26.371	1.108	26.553	26.712	1.245	24.793	25.176	1.862	26.083	26.101	1.333
Debt to GDP (%)	67.717	65.040	23.732	64.239	73.750	26.696	94.243	86.265	34.766	36.826	19.740	32.256	64.347	62.790	35.724
Fiscal balance to GDP (%)	1.362	0.960	3.925	-1.337	-1.390	3.386	-2.876	-3.060	3.031	-1.618	-2.050	3.189	-1.242	-1.430	3.641
GDP growth (%)	1.785	1.656	3.594	1.667	1.587	2.558	1.670	1.441	4.026	2.787	2.753	4.378	1.975	1.766	3.652

PANEL B Period "during and after crisis - DAC" (2007:Q3-2018:Q1)

	Below 25th percentile			Between 25th & 50th percentile			Between 50th & 75th percentile			Above 75th percentile			Total sample		
CORRUPTION CUT-OFF		**-1.670**			**-1.112**			**-0.139**			**-**			**-**	
VARIABLE NAME	*Mean*	*Median*	*St.Dev*	*Mean*	*Median*	*St.Dev*	*Mean*	*Median*	*St.Dev*	*Mean*	*Median*	*St.Dev*	*Mean*	*Median*	*St.Dev*
Price to book	1.478	1.404	0.549	1.205	1.134	0.644	0.995	0.923	0.463	1.120	0.943	0.776	1.158	1.042	0.629
Public sector corruption	-1.996	-1.912	0.255	-1.362	-1.369	0.150	-0.827	-0.946	0.283	0.458	0.498	0.263	-0.818	-1.000	0.893
Dividend payout ratio (%)	6.375	5.987	3.776	4.953	4.496	4.049	2.691	2.166	2.455	2.925	2.564	1.998	3.870	2.985	3.339
Expected growth (%)	2.503	2.983	2.562	1.855	2.499	3.160	1.539	1.947	3.177	3.673	4.293	3.464	2.319	2.612	3.255
Cost of equity (%)	4.990	4.519	2.078	4.840	4.259	2.706	5.575	5.145	2.155	9.876	8.188	7.796	6.297	5.157	4.663
Sigma RoE (%)	1.479	0.809	1.912	1.766	0.789	2.230	1.717	0.965	2.260	1.655	0.915	1.990	1.665	0.904	2.128
Leverage	21.646	21.145	7.640	22.648	18.546	12.099	17.526	14.441	11.981	15.160	15.098	3.905	18.664	16.640	10.183
Opacity	-1.800	-1.619	0.984	-2.203	-2.132	1.059	-1.955	-1.773	1.083	-3.277	-2.972	1.730	-2.274	-1.942	1.360
Size	26.879	26.794	0.618	27.490	27.391	0.742	27.053	27.210	1.343	26.635	26.778	1.610	26.996	27.087	1.257
Debt to GDP (%)	55.857	48.780	26.929	85.800	85.460	41.020	120.032	124.230	43.931	44.489	17.315	43.472	82.254	79.520	51.696
Fiscal balance to GDP (%)	0.351	-0.220	3.815	-2.675	-1.990	4.247	-5.863	-5.260	3.633	-2.147	-2.400	5.271	-3.149	-3.215	4.838
GDP growth (%)	1.302	1.770	5.118	0.099	0.308	4.114	0.608	1.002	3.441	2.261	2.781	4.657	1.068	1.144	4.315

This table shows descriptive statistics per corruption quartile for the period "before crisis - BC" (Panel A) and "during and after crisis - DAC" (Panel B). Quartile cut-offs are calculated using annual frequency at country level. Variables are winsorized at the 0.5^{th} and 99.5^{th} percentile, with the exception of public sector corruption, size, GDP growth, debt to GDP, and fiscal balance to GDP.

TABLE 4 Estimated unrestricted error-correction models for price-to-book using bounds testing for the existence of long-term relationship (1998:Q1-2018:Q1)

Model 1:

$$\Delta PB_{i,t} = \overbrace{\varphi \cdot PB_{i,t-1}}^{Error-correction} + \overbrace{\alpha_0 \cdot \Delta GC_{i,t} + \boldsymbol{\beta}_0 \cdot \Delta \boldsymbol{X}_{i,t}}^{Short-run} + \overbrace{\alpha \cdot GC_{i,t-1} + \boldsymbol{\beta} \cdot \boldsymbol{X}_{i,t-1}}^{Long-run} + c + c_i + c_t + u_{i,t}$$

Model 2:

$$\Delta PB_{i,t} = BC \cdot \left[\overbrace{\varphi_{BC} \cdot PB_{i,t-1}}^{Error-correction\ before\ crisis\ (BC)} + \overbrace{\alpha_{0,BC} \cdot \Delta GC_{i,t} + \boldsymbol{\beta}_{0,BC} \cdot \Delta \boldsymbol{X}_{i,t}}^{Short-run\ before\ crisis\ (BC)} + \overbrace{\alpha_{BC} \cdot GC_{i,t-1} + \boldsymbol{\beta}_{BC} \cdot \boldsymbol{X}_{i,t-1}}^{Long-run\ before\ crisis\ (BC)} + c_{BC} \right] +$$

$$DAC \cdot \left[\overbrace{\varphi_{DAC} \cdot PB_{i,t-1}}^{Error-correction\ during/after\ crisis\ (DAC)} + \overbrace{\alpha_{0,DAC} \cdot \Delta GC_{i,t} + \boldsymbol{\beta}_{0,DAC} \cdot \Delta \boldsymbol{X}_{i,t}}^{Short-run\ during/after\ crisis\ (DAC)} + \overbrace{\alpha_{DAC} \cdot GC_{i,t-1} + \boldsymbol{\beta}_{DAC} \cdot \boldsymbol{X}_{i,t-1}}^{Long-run\ during/after\ crisis\ (DAC)} + c_{DAC} \right] + c_i + c_t + u_{i,t}$$

Model 3:

$$\Delta PB_{i,t} = BC \cdot \left[\overbrace{\varphi_{BC} \cdot PB_{i,t-1} + \varphi_{1,BC} \cdot GC_{i,t} \cdot PB_{i,t-1}}^{Error-correction\ before\ crisis\ (BC)} + \overbrace{\alpha_{0,BC} \cdot \Delta GC_{i,t} + \boldsymbol{\beta}_{0,BC} \cdot \Delta \boldsymbol{X}_{i,t} + \boldsymbol{\gamma}_{0,BC} \cdot GC_{i,t} \cdot \Delta \boldsymbol{X}_{i,t}}^{Short-run\ before\ crisis\ (BC)} + \overbrace{\alpha_{BC} \cdot GC_{i,t-1} + \boldsymbol{\beta}_{BC} \cdot \boldsymbol{X}_{i,t-1} + \boldsymbol{\gamma}_{BC} \cdot GC_{i,t} \cdot \boldsymbol{X}_{i,t-1}}^{Long-run\ before\ crisis\ (BC)} + c_{BC} \right] +$$

$$DAC \cdot \left[\overbrace{\varphi_{DAC} \cdot PB_{i,t-1} + \varphi_{1,DAC} \cdot GC_{i,t} \cdot PB_{i,t-1}}^{Error-correction\ during/after\ crisis\ (DAC)} + \overbrace{\alpha_{0,DAC} \cdot \Delta GC_{i,t} + \boldsymbol{\beta}_{0,DAC} \cdot \Delta \boldsymbol{X}_{i,t} + \boldsymbol{\gamma}_{0,DAC} \cdot GC_{i,t} \cdot \Delta \boldsymbol{X}_{i,t}}^{Short-run\ during/after\ crisis\ (DAC)} + \overbrace{\alpha_{DAC} \cdot GC_{i,t-1} + \boldsymbol{\beta}_{DAC} \cdot \boldsymbol{X}_{i,t-1} + \boldsymbol{\gamma}_{DAC} \cdot GC_{i,t} \cdot \boldsymbol{X}_{i,t-1}}^{Long-run\ during/after\ crisis\ (DAC)} + c_{DAC} \right] + c_i + c_t + u_{i,t}$$

		MODEL 1: ONE REGIME	MODEL 2: NO CORRUPTION INTERACTIONS		MODEL 3: CORRUPTION INTERACTIONS			
	Covariates		Before Crisis (BC=1, DAC=0)	During/After Crisis (BC=0, DAC=1)	Before Crisis (BC=1, DAC=0)		During/After Crisis (BC=0, DAC=1)	
					Direct	*Interact*	*Direct*	*Interact*
Short-run (first differences)	Corruption (direct effect)	0.210**	0.199	0.235**	0.383	–	1.323***	–
	Dividend payout ratio (DPR)	0.028***	0.023***	0.028***	0.008	-0.017*	0.013**	-0.013***
	Expected growth	-0.001	0.003	-0.001	0.001	-0.002	-0.007***	-0.007***
	Cost of equity	-0.006***	0.000	-0.005***	0.003	0.004	-0.004*	-0.005***
	Sigma RoE	-0.015***	-0.027***	-0.010**	-0.067***	-0.040***	-0.020***	-0.013*
	Leverage	0.022***	0.052***	0.016***	0.060***	0.008	0.009***	-0.006***
	Opacity	-0.012***	0.007	-0.016***	0.016	0.006	-0.004	0.035***
	Size	-0.603***	-0.860***	-0.545***	-0.619***	0.226**	-0.211*	0.300***
	GDP growth	0.004***	0.007***	0.003***	0.004	-0.001	0.001	-0.003**
Long-run (lagged levels)	Corruption (direct effect)	0.020	0.052***	0.008	0.332	–	1.147***	–
	Dividend payout ratio (DPR)	0.007***	0.002	0.010***	-0.008	-0.010**	0.009***	-0.004*
	Expected growth	-0.002	0.001	-0.004**	-0.002	-0.005	-0.010***	-0.008***
	Cost of equity	-0.001	-0.007***	0.001	-0.005**	-0.002	-0.000	0.001
	Sigma RoE	-0.006***	-0.006	-0.005**	-0.002	0.001	-0.008**	-0.004
	Leverage	0.004***	0.006***	0.002***	0.006***	0.000	0.003**	0.002
	Opacity	0.010***	0.010*	0.014***	0.016*	0.003	0.012**	-0.004
	Size	-0.069***	-0.082***	-0.094***	-0.079***	-0.014	-0.112***	-0.045***
	GDP growth	0.003**	0.007**	0.002	0.006	0.001	-0.001	-0.004***
	Error-correction term	-0.147***	-0.120***	-0.192***	-0.040*	0.078***	-0.195***	0.033***
	Constant	1.862***	2.063***	2.337***	1.842***		2.750***	

Observations	–	4,281		
Adjusted R^2	–	44.8%	47.6%	49.5%
Bank / Time effects	–	Yes / Yes		

This table shows estimation results for unrestricted error-correction models for price-to-book and covariates. Models 1 to 3 include, but do not report, bank-specific and time effects. Estimation points include observations from 77 banks (*i*) over 72 quarters (*t*). For Model 3 and for the periods "before crisis - BC" (1998:Q1-2007:Q2) and "during and after crisis - DAC" (2007:Q3-2018:Q1), the left column corresponds to variable coefficients (direct effects) and the right column reports interaction effects of variables with corruption. Statistical significance at 1%, 5% and 10% level is denoted by ***, ** and * respectively. Statistical significance for first differences (short-run effects) and constant terms are based on standard inference. For lagged levels (long-run effects) and the error-correction parameter the statistical significance is based on the panel bounds testing procedure of Bertsatos et al. (2022b), which extends the bounds testing procedure for time series by Pesaran et al. (2001) and Bertsatos et al. (2022a), as discussed in Appendix B.

TABLE 5.A Marginal and economic effect of variables on price-to-book ratio per corruption percentiles, before the crisis (1998:Q1-2007:Q2)

$$\Delta\widehat{PB}_{i,t} = \hat{\varphi}\cdot PB_{i,t-1} + \hat{\varphi}_1\cdot GC_{i,t}\cdot PB_{i,t-1} + \hat{\alpha}\cdot GC_{i,t-1} + \widehat{\boldsymbol{\beta}}\cdot \boldsymbol{X}_{i,t-1} + \widehat{\boldsymbol{\gamma}}\cdot GC_{i,t}\cdot \boldsymbol{X}_{i,t-1} + \hat{\alpha}_0\cdot \Delta GC_{i,t} + \widehat{\boldsymbol{\beta}}_0\cdot \Delta\boldsymbol{X}_{i,t} + \widehat{\boldsymbol{\gamma}}_0\cdot GC_{i,t}\cdot \Delta\boldsymbol{X}_{i,t} + \hat{c}_{BC} + \hat{c}_i + \hat{c}_t$$

CORRUPTION PERCENTILES		Below 25th percentile		Between 25th & 50th percentile		Between 50th & 75th percentile		Above 75th percentile	
Mean corruption across estimation points		-2.263		-1.391		-0.753		0.416	
		Marginal effect	Economic effect	Marginal effect	Economic effect	Marginal effect	Economic effect	Marginal effect	Economic effect
Short run effects	Corruption (direct effect)	0.383	0.098	0.383	0.121	0.383	0.127	0.383	0.112
	Dividend payout ratio (DPR)	0.048***	0.113	0.032***	0.117	0.021***	0.061	0.001	0.003
	Expected growth	0.006	0.009	0.004	0.009	0.003	0.009	0.000	0.001
	Cost of equity	-0.006	-0.008	-0.002	-0.003	0.000	0.000	0.005	0.057
	Sigma RoE	0.024	0.016	-0.011	-0.020	-0.036***	-0.092	-0.083***	-0.220
	Leverage	0.042***	0.397	0.049***	0.488	0.054***	0.724	0.064***	0.425
	Opacity	0.002	0.002	0.007	0.008	0.011	0.014	0.019	0.031
	Size	-1.131***	-0.881	-0.934***	-1.012	-0.790***	-1.087	-0.525***	-0.833
	GDP growth	0.005	0.021	0.005*	0.012	0.004*	0.013	0.003	0.017
Long run effects	Corruption (direct effect)	1.534	0.393	2.240	0.705	3.374	1.120	47.078	13.747
	Dividend payout ratio (DPR)	0.062***	0.148	0.035**	0.125	-0.010	-0.028	-1.729	-4.088
	Expected growth	0.044	0.062	0.034	0.071	0.017	0.050	-0.629	-1.484
	Cost of equity	-0.004	-0.005	-0.018	-0.021	-0.040	-0.060	-0.897	-9.683
	Sigma RoE	-0.021	-0.015	-0.025	-0.045	-0.031	-0.078	-0.247	-0.656
	Leverage	0.026***	0.241	0.040***	0.393	0.062***	0.827	0.926	6.194
	Opacity	0.041	0.059	0.079**	0.092	0.141**	0.180	2.521	4.275
	Size	-0.216**	-0.168	-0.399***	-0.433	-0.693***	-0.954	-12.029	-19.065
	GDP growth	0.019	0.073	0.032*	0.078	0.053**	0.160	0.844	4.286
Error-correction term		-0.217***		-0.148***		-0.098***		-0.007	
Constant		1.842***							
Number of estimation points		**243**		**612**		**240**		**110**	

This table shows marginal and economic effects on price-to-book ratio per corruption quartile using the estimated panel ARDL model of equation (8) and focusing on the period before crisis (BC=1 and DAC=0). In each quartile j the short-run marginal effects of characteristics $\boldsymbol{X}$ equal the sum of estimated effects $\widehat{\boldsymbol{\beta}}_0$ of current first differences plus the interaction effects $\widehat{\boldsymbol{\gamma}}_0\cdot\overline{GC}_j$ calculated at the mean corruption level $\overline{GC}_j$ in the quartile: $\widehat{\boldsymbol{\beta}}_0 + \widehat{\boldsymbol{\gamma}}_0\cdot\overline{GC}_j$. The long-run marginal effects equal the sum of estimated effects $\widehat{\boldsymbol{\beta}}$ of lagged levels plus the interaction effects $\widehat{\boldsymbol{\gamma}}\cdot\overline{GC}_j$ at the mean corruption level in the respective quartile, divided by the sum of speed of adjustment $-\hat{\varphi}$ plus its interaction effect $-\hat{\varphi}\cdot\overline{GC}_j$ at mean corruption: $-\left[\widehat{\boldsymbol{\beta}} + \widehat{\boldsymbol{\gamma}}\cdot\overline{GC}_j\right]/\left[\hat{\varphi} + \hat{\varphi}_1\cdot\overline{GC}_j\right]$. Economic effects are calculated as marginal effects multiplied by the standard deviation of respective variables in each quartile. Standard errors are reported in parentheses. Statistical significance at 1%, 5% and 10% level is denoted by ***, ** and * respectively.

TABLE 5.B Marginal and economic effect of variables on price-to-book ratio per corruption percentiles, during and after crisis (2007:Q3-2018:Q1)

$$\Delta\widehat{PB}_{i,t} = \hat{\varphi}\cdot PB_{i,t-1} + \hat{\varphi}_1\cdot GC_{i,t}\cdot PB_{i,t-1} + \hat{\alpha}\cdot GC_{i,t-1} + \widehat{\boldsymbol{\beta}}\cdot \boldsymbol{X}_{i,t-1} + \widehat{\boldsymbol{\gamma}}\cdot GC_{i,t}\cdot \boldsymbol{X}_{i,t-1} + \hat{\alpha}_0\cdot \Delta GC_{i,t} + \widehat{\boldsymbol{\beta}}_0\cdot \Delta\boldsymbol{X}_{i,t} + \widehat{\boldsymbol{\gamma}}_0\cdot GC_{i,t}\cdot \Delta\boldsymbol{X}_{i,t} + \hat{c}_{DAC} + \hat{c}_i + \hat{c}_t$$

CORRUPTION PERCENTILES		Below 25th percentile		Between 25th & 50th percentile		Between 50th & 75th percentile		Above 75th percentile	
Mean corruption across estimation points		-1.996		-1.362		-0.854		0.443	
		Marginal effect	Economic effect	Marginal effect	Economic effect	Marginal effect	Economic effect	Marginal effect	Economic effect
Short run effects	Corruption (direct effect)	1.323***	0.337	1.323***	0.198	1.323***	0.344	1.323***	0.332
	Dividend payout ratio (DPR)	0.040***	0.151	0.031***	0.127	0.025***	0.061	0.007	0.014
	Expected growth	0.006**	0.015	0.002	0.005	-0.002	-0.005	-0.010*	-0.037
	Cost of equity	0.005	0.011	0.002	0.007	0.000	0.000	-0.006***	-0.046
	Sigma RoE	0.005	0.010	-0.003	-0.006	-0.009*	-0.020	-0.026***	-0.053
	Leverage	0.020***	0.153	0.017***	0.200	0.014***	0.164	0.007*	0.027
	Opacity	-0.075***	-0.073	-0.052***	-0.055	-0.034***	-0.037	0.012	0.021
	Size	-0.810***	-0.500	-0.620***	-0.460	-0.467***	-0.624	-0.078	-0.132
	GDP growth	0.006***	0.032	0.005***	0.019	0.003***	0.010	-0.000	-0.001
Long run effects	Corruption (direct effect)	4.413***	1.125	4.795***	0.719	5.153***	1.340	6.368***	1.598
	Dividend payout ratio (DPR)	0.066***	0.251	0.061***	0.245	0.055***	0.136	0.037*	0.070
	Expected growth	0.025**	0.063	0.006	0.018	-0.012*	-0.039	-0.073***	-0.268
	Cost of equity	-0.011	-0.023	-0.008	-0.023	-0.006	-0.011	0.003	0.025
	Sigma RoE	-0.002	-0.004	-0.012	-0.027	-0.022**	-0.048	-0.054**	-0.112
	Leverage	0.002	0.012	0.006*	0.069	0.010***	0.116	0.023**	0.094
	Opacity	0.077***	0.076	0.074***	0.078	0.070***	0.077	0.059*	0.105
	Size	-0.082	-0.051	-0.209***	-0.155	-0.328***	-0.438	-0.730***	-1.230
	GDP growth	0.027***	0.138	0.019***	0.078	0.011*	0.036	-0.014	-0.069
Error-correction term		-0.260***		-0.239***		-0.223***		-0.180***	
Constant		2.750***							
Number of estimation points		**625**		**612**		**1163**		**676**	

This table shows marginal and economic effects on price-to-book ratio per corruption quartile using the estimated panel ARDL model of equation (8) and focusing on the period during and after crisis (BC=0 and DAC=1). In each quartile j the short-run marginal effects of characteristics $\boldsymbol{X}$ equal the sum of estimated effects $\widehat{\boldsymbol{\beta}}_0$ of current first differences plus the interaction effects $\widehat{\boldsymbol{\gamma}}_0\cdot\overline{GC}_j$ calculated at the mean corruption level $\overline{GC}_j$ in the quartile: $\widehat{\boldsymbol{\beta}}_0 + \widehat{\boldsymbol{\gamma}}_0\cdot\overline{GC}_j$. The long-run marginal effects equal the sum of estimated effects $\widehat{\boldsymbol{\beta}}$ of lagged levels plus the interaction effects $\widehat{\boldsymbol{\gamma}}\cdot\overline{GC}_j$ at the mean corruption level in the respective quartile, divided by the sum of speed of adjustment $-\hat{\varphi}$ plus its interaction effect $-\hat{\varphi}\cdot\overline{GC}_j$ at mean corruption: $-\left[\widehat{\boldsymbol{\beta}} + \widehat{\boldsymbol{\gamma}}\cdot\overline{GC}_j\right]/\left[\hat{\varphi} + \hat{\varphi}_1\cdot\overline{GC}_j\right]$. Economic effects are calculated as marginal effects multiplied by the standard deviation of respective variables in each quartile. Standard errors are reported in parentheses. Statistical significance at 1%, 5% and 10% level is denoted by ***, ** and * respectively.

TABLE 6 Effect on level playing field in bank valuations due to public-sector corruption

PANEL A Period "before crisis - BC" (1998:Q1-2007:Q2)

Originating regime \ Destination regime	1st corruption quartile (q=1)	2nd corruption quartile (q=2)	3rd corruption quartile (q=3)	4th corruption quartile (q=4)
1st corruption quartile	-	0.220*** (0.020)	0.582*** (0.053)	*NC*
2nd corruption quartile	-0.183*** (0.020)	-	0.234*** (0.026)	*NC*
3rd corruption quartile	-0.354*** (0.098)	-0.248*** (0.081)	-	*NC*
4th corruption quartile	*NC*	*NC*	*NC*	-

PANEL B Period "during and after crisis - DAC" (2007:Q3-2018:Q1)

Originating regime \ Destination regime	1st corruption quartile (q=1)	2nd corruption quartile (q=2)	3rd corruption quartile (q=3)	4th corruption quartile (q=4)
1st corruption quartile	-	-0.070*** (0.003)	-0.145*** (0.006)	-0.401*** (0.017)
2nd corruption quartile	0.123*** (0.005)	-	-0.110*** (0.003)	-0.492*** (0.016)
3rd corruption quartile	0.138*** (0.012)	0.054*** (0.008)	-	-0.287*** (0.013)
4th corruption quartile	0.296*** (0.032)	0.241*** (0.025)	0.190*** (0.019)	-

This table shows the effect on level playing field in bank valuations as a result of public-sector corruption before the crisis (Panel A), and during and after crisis (Panel B). We use hypothetical scenarios where banks migrate from domicile regimes to different corruption quartiles. For each bank i with characteristics $\boldsymbol{X}_{i,t}$ at time t, let $\widehat{PB}_{i,t,q}^{LR}$ the long-run PB calculated at average corruption level at destination quartile q, as of equation (10). Let also $\widehat{PB}_{i,t}^{LR}$ the in-sample point estimate of long-run PB at destination quartile, as of equation (11). The corruption effect is measured by the pooled average difference $\widehat{PB}_{i,t,q}^{LR} - \widehat{PB}_{i,t}^{LR}$. Standard errors are reported in parentheses. Statistical significance at 1%, 5% and 10% level is denoted by ***, ** and * respectively. *NC* denotes no co-integration.

Appendix

A. Endogeneity controls

The ARDL framework involves estimation of both short- and long-run responses of PB to covariates, allowing for mixtures of $I(0)$ and $I(1)$ regressors. Given that standard inference for the existence of a cointegrating relationship does not apply in this case, we use a panel bounds testing procedure, as discussed in Appendix B. In such a context, covariates may be both temporary and permanent Granger-causals of PB. In addition, PB may be a short-run Granger-causal of covariates, in which case the error-projection mechanism is used to control for endogeneity (Cho et al., 2015; Shin et al., 2014; Pesaran et al., 2001; Pesaran and Shin, 1999).[16]

We allow for the possibility of endogenous regressors in Model 3 (see Table 4) by employing error projection of its residuals $u_{i,t}$ on the residuals $\boldsymbol{\eta}_{i,t}$ of marginal equation (A1) for covariates $\boldsymbol{Z}_{i,t} \equiv \left(GC_{i,t}, \boldsymbol{X}_{i,t}\right)$.

$$\Delta \boldsymbol{Z}_{i,t} = BC \cdot \sum_{j=1}^{3}\left(\boldsymbol{w}_{j,BC} + \boldsymbol{q}_{j,BC} \cdot GC_{i,t}\right) \cdot \Delta PB_{i,t-j} + DAC \cdot \sum_{j=1}^{3}\left(\boldsymbol{w}_{j,DAC} + \boldsymbol{q}_{j,DAC} \cdot GC_{i,t}\right) \cdot \Delta PB_{i,t-j} + \boldsymbol{\eta}_{i,t} \tag{A1}$$

$$u_{i,t} = \boldsymbol{h} \cdot \boldsymbol{\eta}_{i,t} + \upsilon_{i,t} \tag{A2}$$

where, $u_{i,t}$ is the residual term in Model 3, $\boldsymbol{\eta}_{i,t}$ is a vector of multivariate uncorrelated errors, and $\upsilon_{i,t}$ is uncorrelated with $\boldsymbol{\eta}_{i,t}$ by construction.

Such a parametric correction of endogeneity in $\boldsymbol{Z}_{i,t}$ is equivalent to extending Model 3 from a panel ARDL(0,**0**) to a panel ARDL (3,**0**) in unrestricted error-correction form, as follows. Given quarterly data, we use three lags of changes in PB to capture feedback effects up to one year.

$$\begin{aligned}
\Delta PB_{i,t} = BC \cdot &\left[\overbrace{\left(\varphi_{BC} + \varphi_{1,BC} \cdot GC_{i,t}\right) \cdot PB_{i,t-1}}^{Error-correction\ before\ crisis\ (BC)} + \overbrace{\left[\begin{matrix} a'_{0,BC} \cdot \Delta GC_{i,t} + \left(\boldsymbol{\beta}'_{0,BC} + \boldsymbol{\gamma}'_{0,BC} \cdot GC_{i,t}\right) \cdot \Delta \boldsymbol{X}_{i,t} \\ + \sum_{j=1}^{3}\left(\delta_{j,BC} + \zeta_{j,BC} \cdot GC_{i,t}\right) \cdot \Delta PB_{i,t-j} \end{matrix}\right]}^{Short-run\ before\ crisis\ (BC)} + \overbrace{\alpha_{BC} \cdot GC_{i,t-1} + \left(\boldsymbol{\beta}_{BC} + \boldsymbol{\gamma}_{BC} \cdot GC_{i,t}\right) \cdot \boldsymbol{X}_{i,t-1}}^{Long-run\ before\ crisis\ (BC)} \right] + \\
DAC \cdot &\left[\overbrace{\left(\varphi_{DAC} + \varphi_{1,DAC} \cdot GC_{i,t}\right) \cdot PB_{i,t-1}}^{Error-correction\ during/after\ crisis\ (DAC)} + \overbrace{\left[\begin{matrix} a'_{0,DAC} \cdot \Delta GC_{i,t} + \left(\boldsymbol{\beta}'_{0,DAC} + \boldsymbol{\gamma}'_{0,DAC} \cdot GC_{i,t}\right) \cdot \Delta \boldsymbol{X}_{i,t} \\ + \sum_{j=1}^{3}\left(\delta_{j,DAC} + \zeta_{j,DAC} \cdot GC_{i,t}\right) \cdot \Delta PB_{i,t-j} \end{matrix}\right]}^{Short-run\ during/after\ crisis\ (DAC)} + \overbrace{\alpha_{DAC} \cdot GC_{i,t-1} + \left(\boldsymbol{\beta}_{DAC} + \boldsymbol{\gamma}_{DAC} \cdot GC_{i,t}\right) \cdot \boldsymbol{X}_{i,t-1}}^{Long-run\ during/after\ crisis\ (DAC)} \right] \\
&+ BC \cdot c_{BC} + DAC \cdot c_{DAC} + c_i + c_t + \upsilon_{i,t}
\end{aligned} \tag{A3}$$

Table A.1 compares estimated coefficients of Model 3 (columns 3 to 6) with those of extended Model 3 (columns 7 to 10) of equation (A3). We verify trivial differences in statistical significance between the two specifications that we interpret as indication of robustness of the results to short-run endogeneity issues.

[16] In dynamic panels with mixtures of $I(0)$ and $I(1)$ variables controlling for endogeneity also for the long-run would call for a generalized version of panel VECM where standard inference does not apply and possibly new critical values for Toda-Yamamoto type Granger-causality test are required. Such an empirical approach falls beyond the scope of this paper.

TABLE A.1 Estimated unrestricted error-correction model for price-to-book and covariates using bounds testing for the existence of long-term relationship (Model 3) and its extension (Model 3 extended) with the addition of three lags of changes in the dependent variable (1998:Q1-2018:Q1)

Model 3:

$$\Delta PB_{i,t} = BC \cdot \left[\overbrace{\varphi_{BC} \cdot PB_{i,t-1} + \varphi_{1,BC} \cdot GC_{i,t} \cdot PB_{i,t-1}}^{Error-correction\ before\ crisis\ (BC)} + \overbrace{\alpha_{0,BC} \cdot \Delta GC_{i,t} + \boldsymbol{\beta}_{0,BC} \cdot \Delta \boldsymbol{X}_{i,t} + \boldsymbol{\gamma}_{0,BC} \cdot GC_{i,t} \cdot \Delta \boldsymbol{X}_{i,t}}^{Short-run\ before\ crisis\ (BC)} + \overbrace{\alpha_{BC} \cdot GC_{i,t-1} + \boldsymbol{\beta}_{BC} \cdot \boldsymbol{X}_{i,t-1} + \boldsymbol{\gamma}_{BC} \cdot GC_{i,t} \cdot \boldsymbol{X}_{i,t-1}}^{Long-run\ before\ crisis\ (BC)} \right] +$$

$$DAC \cdot \left[\overbrace{\varphi_{DAC} \cdot PB_{i,t-1} + \varphi_{1,DAC} \cdot GC_{i,t} \cdot PB_{i,t-1}}^{Error-correction\ during/after\ crisis\ (DAC)} + \overbrace{\alpha_{0,DAC} \cdot \Delta GC_{i,t} + \boldsymbol{\beta}_{0,DAC} \cdot \Delta \boldsymbol{X}_{i,t} + \boldsymbol{\gamma}_{0,DAC} \cdot GC_{i,t} \cdot \Delta \boldsymbol{X}_{i,t}}^{Short-run\ during/after\ crisis\ (DAC)} + \overbrace{\alpha_{DAC} \cdot GC_{i,t-1} + \boldsymbol{\beta}_{DAC} \cdot \boldsymbol{X}_{i,t-1} + \boldsymbol{\gamma}_{DAC} \cdot GC_{i,t} \cdot \boldsymbol{X}_{i,t-1}}^{Long-run\ during/after\ crisis\ (DAC)} \right] + BC \cdot c_{BC} + DAC \cdot c_{DAC} + c_i + c_t + u_{i,t}$$

Model 3 extended:

$$\Delta PB_{i,t} = BC \cdot \left[\overbrace{\left(\varphi_{BC} + \varphi_{1,BC} \cdot GC_{i,t}\right) \cdot PB_{i,t-1}}^{Error-correction\ before\ crisis\ (BC)} + \overbrace{\begin{bmatrix} \alpha'_{0,BC} \cdot \Delta GC_{i,t} + \left(\boldsymbol{\beta}'_{0,BC} + \boldsymbol{\gamma}'_{0,BC} \cdot GC_{i,t}\right) \cdot \Delta \boldsymbol{X}_{i,t} \\ + \sum_{j=1}^{3} \left(\delta_{j,BC} + \zeta_{j,BC} \cdot GC_{i,t}\right) \cdot \Delta PB_{i,t-j} \end{bmatrix}}^{Short-run\ before\ crisis\ (BC)} + \overbrace{\alpha_{BC} \cdot GC_{i,t-1} + \left(\boldsymbol{\beta}_{BC} + \boldsymbol{\gamma}_{BC} \cdot GC_{i,t}\right) \cdot \boldsymbol{X}_{i,t-1}}^{Long-run\ before\ crisis\ (BC)} \right] +$$

$$DAC \cdot \left[\overbrace{\left(\varphi_{DAC} + \varphi_{1,DAC} \cdot GC_{i,t}\right) \cdot PB_{i,t-1}}^{Error-correction\ during/after\ crisis\ (DAC)} + \overbrace{\begin{bmatrix} \alpha'_{0,DAC} \cdot \Delta GC_{i,t} + \left(\boldsymbol{\beta}'_{0,DAC} + \boldsymbol{\gamma}'_{0,DAC} \cdot GC_{i,t}\right) \cdot \Delta \boldsymbol{X}_{i,t} \\ + \sum_{j=1}^{3} \left(\delta_{j,DAC} + \zeta_{j,DAC} \cdot GC_{i,t}\right) \cdot \Delta PB_{i,t-j} \end{bmatrix}}^{Short-run\ during/after\ crisis\ (DAC)} + \overbrace{\alpha_{DAC} \cdot GC_{i,t-1} + \left(\boldsymbol{\beta}_{DAC} + \boldsymbol{\gamma}_{DAC} \cdot GC_{i,t}\right) \cdot \boldsymbol{X}_{i,t-1}}^{Long-run\ during/after\ crisis\ (DAC)} \right] + BC \cdot c_{BC} + DAC \cdot c_{DAC} + c_i + c_t + v_{i,t}$$

		MODEL 3: CORRUPTION INTERACTIONS				**MODEL 3A: CORRUPTION INTERACTIONS**			
	Covariates	Before Crisis (BC=1, DAC=0)		During/After Crisis (BC=0, DAC=1)		Before Crisis (BC=1, DAC=0)		During/After Crisis (BC=0, DAC=1)	
		Direct	*Interact*	*Direct*	*Interact*	*Direct*	*Interact*	*Direct*	*Interact*
Short-run (first differences)	Corruption (direct effect)	0.383	–	1.323^{***}	–	0.507	–	1.549^{***}	–
	Dividend payout ratio (DPR)	0.008	-0.017^{*}	0.013^{**}	-0.013^{***}	0.009	-0.017^{*}	0.013^{**}	-0.013^{***}
	Expected growth	0.001	-0.002	-0.007^{***}	-0.007^{***}	0.001	-0.002	-0.006^{***}	-0.006^{***}
	Cost of equity	0.003	0.004	-0.004^{*}	-0.005^{***}	0.003	0.005	-0.005^{***}	-0.004^{**}
	Sigma RoE	-0.067^{***}	-0.040^{***}	-0.020^{***}	-0.013^{*}	-0.064^{***}	-0.037^{***}	-0.016^{**}	-0.009
	Leverage	0.060^{***}	0.008	0.009^{***}	-0.006^{***}	0.057^{***}	0.006	0.010^{***}	-0.005^{**}
	Opacity	0.016	0.006	-0.004	0.035^{***}	0.016	0.006	-0.008	0.033^{***}
	Size	-0.619^{***}	0.226^{**}	-0.211^{*}	0.300^{***}	-0.609^{***}	0.235^{**}	-0.228^{*}	0.276^{***}
	GDP growth	0.004	-0.001	0.001	-0.003^{**}	0.002	-0.001	0.001	-0.003^{***}
	PB(-1)	–	–	–	–	0.047	0.027	0.141^{***}	0.131^{***}
	PB(-2)	–	–	–	–	0.082^{**}	0.049	-0.093^{***}	-0.026
	PB(-3)	–	–	–	–	-0.055	-0.045	-0.030	0.001
Long-run (lagged levels)	Corruption (direct effect)	0.332	–	1.147^{***}	–	0.458	–	1.323^{***}	–
	Dividend payout ratio (DPR)	-0.008	-0.010^{**}	0.009^{***}	-0.004^{*}	-0.006	-0.008^{*}	0.008^{**}	-0.004^{*}
	Expected growth	-0.002	-0.005	-0.010^{***}	-0.008^{***}	-0.001	-0.005	-0.007^{***}	-0.005^{**}

	Cost of equity	-0.005**	-0.002	-0.000	0.001	-0.006**	-0.003	-0.001	0.000
	Sigma RoE	-0.002	0.001	-0.008**	-0.004	-0.003	0.000	-0.008**	-0.002
	Leverage	0.006***	0.000	0.003**	0.002	0.007***	0.001	0.004***	0.002**
	Opacity	0.016*	0.003	0.012**	-0.004	0.016*	0.004	0.008	-0.007
	Size	-0.079***	-0.014	-0.112***	-0.045***	-0.087***	-0.018	-0.122***	-0.052***
	GDP growth	0.006	0.001	-0.001	-0.004***	0.004	0.000	-0.002	-0.005***
	Error-correction term	-0.040*	0.078***	-0.195***	0.033***	-0.067**	0.057***	-0.196***	0.023**
	Constant	1.842***		2.750***		2.021***		2.962***	
Observations	–	4,281				4,281			
Adjusted R^2	–	49.5%				50.6%			
Bank / Time effects	–	Yes / Yes							

This table shows estimation results for the unrestricted error-correction model for price-to-book and covariates using bounds testing for the existence of long-term relationship (Model 3) and its extension (Model 3 extended) with the addition of three lags of changes in the dependent variable. Estimated models include, but do not report, bank-specific and time effects. Estimation points include observations from 77 banks (i) over 72 quarters (t). For each model and for the periods "before crisis - BC" (1998:Q1-2007:Q2) and "during and after crisis - DAC" (2007:Q3-2018:Q1), the left column corresponds to variable coefficients (direct effects) and the right column reports interaction effects of variables with corruption. Statistical significance at 1%, 5% and 10% level is denoted by ***, ** and * respectively. Statistical significance for first differences (short-run effects) and constant terms are based on standard inference. For lagged levels (long-run effects) and the error-correction parameter the statistical significance is based on the panel bounds testing procedure of Bertsatos et al. (2022b), which extends the bounds testing procedure for time series by Pesaran et al. (2001) and Bertsatos et al. (2022a), as discussed in Appendix B.

B. Bounds testing procedure for long-run effects

Before analyzing long-run effects between PB and its covariates we establish whether an equilibrium path actually exists using a battery of tests known as panel bounds testing procedure. We employ the panel bounds testing procedure of Bertsatos et al. (2022b) that extends Pesaran et al. (2001) and Bertsatos et al. (2022a) as applied to time-series.

ARDL models may include mixtures of $I(0)$ and $I(1)$ variables so standard inference does not apply. We derive sample- and lag-specific critical values for Model 1 (see Table 4) using Monte Carlo simulations with 10,000 replications for $k = 9$ regressors, $N = 77$ cross-sections and $T = 72$ time periods. For the data generation process we employ the standard normal distribution. As a robustness check, we also use student-t distribution with five degrees of freedom and bounds testing results remain qualitatively unaltered.

We first conduct panel unit-root tests to confirm that none of the variables is $I(2)$ or integrated of higher order. Table B.1 shows that none of our variables contain a unit root in first differences.

TABLE B.1 Panel unit-root tests for model variables

	IPS	Choi, Fisher	Choi, PP	MW, Fisher	MW, PP
Δ(price to book)	-55.51***	-39.31***	-42.67***	2058.99***	2313.79***
Δ(corruption)	-11.54***	-11.56***	-16.31***	398.84***	565.39***
Δ(sigma RoE)	-47.26***	-38.52***	-39.69***	1968.05***	2028.85***
Δ(cost of equity)	-48.68***	-40.34***	-41.58***	2098.52***	2200.70***
Δ(dividend payout ratio)	-59.57***	-42.09***	-44.47***	2320.90***	2490.48***
Δ(expected growth)	-69.61***	-44.36***	-44.74***	2647.36***	2818.49***
Δ(leverage)	-58.63***	-40.27***	-41.99***	2157.70***	2271.24***
Δ(size)	-45.72***	-35.80***	-38.95***	1781.76***	1968.60***
Δ(opacity)	-55.56***	-41.37***	-43.69***	2202.79***	2403.08***
Δ(GDP growth)	-60.88***	-46.64***	-44.34***	2613.45***	2504.19***

This table reports test statistics for alternative panel unit-root tests of model variables. "IPS" denotes the Im-Pesaran-Shin (2003) panel unit-root test, "Choi, Fisher" and "MW, Fisher" the Fisher-type tests of Choi (2001), and Maddala-Wu (1999), while "Choi, PP" and "MW, PP" the Phillips-Perron type tests of Choi (2001), and Maddala-Wu (1999). All tests are Dickey-Fuller type allowing for an intercept and heterogeneous autoregressive parameters. Under the null hypothesis, all panels contain a unit root, for the alternative that a non-zero fraction of the individual processes is stationary. Statistical significance at 1%, 5% and 10% level is denoted by ***, ** and * respectively.

Having established there is no *I(2)* variable in our dataset we examine if the effects of the lagged dependent variable in levels $PB_{i,t-1}$, lagged independent variables $GC_{i,t-1}$, $\boldsymbol{X}_{i,t-1}$ in levels and the intercept are jointly zero using a F-test. This is referred as $F_{\mathbf{yx}}$-test (Case II), following Bertsatos et al. (2022b). If the $F_{\mathbf{yx}}$-test rejects the null of jointly zero effects, we test for the effect of $PB_{i,t-1}$ using a left-sided t-test (t_{y}-test). If it rejects the null of zero $PB_{i,t-1}$ effect (for the alternative of negative values) we repeat the above $F_{\mathbf{yx}}$-test but excluding this time the effect of $PB_{i,t-1}$ ($F_{\mathbf{x}}$-test). A non-degenerate long-term relationship exists if the null of joint insignificance of lagged independent variables in levels is rejected. The long-run relationship is also stable if the error-correction coefficient (φ) takes values in the range (-2, 0). The significance of long-run effects is then tested using the delta method.[17]

If the $F_{\mathbf{x}}$-test does not reject the null of joint insignificance of lagged independent variables, we use a t-test for each of the lagged independent variable in levels ($t_{\mathbf{x}}$-tests). If any of the $t_{\mathbf{x}}$-tests is found to be significant, we test the

[17] The delta method is valid here since the panel has relatively large time and cross-sectional dimension.

significance of the long-run effects using the delta method. $F_{\mathbf{x}}$-test and $t_{\mathbf{x}}$-tests allow to discern degenerate from non-degenerate co-integrating relationships in case the numerator of the long-run effect is zero.[18] For robustness, we also test for co-integration when the constant term is not included in the joint null of the above $F_{\mathrm{y}\mathbf{x}}$-test and $F_{\mathbf{x}}$-test, referred as Case III following Bertsatos et al. (2022b).[19]

Bounds testing involves two critical values for any given level of statistical significance: one for $I(0)$ and another for $I(1)$ type of regressors. To be conservative, in each step of the bounds testing procedure we consider the highest absolute critical value to avoid overrejection of the null. In addition, Models 2 and 3 (see Table 4) include interaction terms that increase the number of regressors. For these models we apply the bounds testing procedure in a conservative way by using the initial number of regressors ($k = 9$) in the baseline Model 1 given that the critical values for the F-tests fall with k.[20] We also produce simulated critical values for two-sided t-tests for the independent variable in levels ($t_{\mathbf{x}}$-tests). To be conservative also in this case, we consider the maximum absolute critical value across variables for each side of the $t_{\mathbf{x}}$-tests.

TABLE B.2 Simulated critical values and test statistics of bounds testing procedure for Models 1 to 3

	Simulated critical values for different significance levels			Test statistics of alternative models				
	10%	5%	1%	Model 1	Model 2		Model 3	
$F_{\mathrm{y}\mathbf{x}}$-test – Case II	1.582	1.804	2.298	53.198	32.573		19.115	
$F_{\mathrm{y}\mathbf{x}}$-test – Case III	1.606	1.840	2.362	55.451	33.342		19.478	
$F_{\mathbf{x}}$-test – Case II	1.609	1.857	2.359	29.812	16.159		9.619	
$F_{\mathbf{x}}$-test – Case III	1.634	1.888	2.461	10.472	9.704		6.772	
left-sided t_{y}-test	-1.723	-2.068	-2.821	-21.821	-13.525	-20.558	-1.936	-17.912
right-sided t_{y}-test	1.218	1.556	2.254	–	–	–	4.731	3.338

This table presents simulated critical values for different significance levels and test statistics for Models 1-3. Bounds testing involves two critical values for given level of statistical significance, i.e. one for $I(0)$ and another for $I(1)$ type of regressors. To be conservative, we consider the highest absolute critical value to avoid overrejection of the null. Columns 2 to 4 report for each test critical values at 10%, 5% and 1% significance level. Columns 5 to 7 show test statistics for Models 1 to 3. The left column in Model 2 and 3 for the t_{y}-test corresponds to the regime "before crisis", while the right column to "during and after crisis". $F_{\mathrm{y}\mathbf{x}}$-test – Case II examines the joint significance of lagged dependent variable in levels, lagged independent variables in levels and the constant term. $F_{\mathrm{y}\mathbf{x}}$-test – Case III excludes the constant term from the test of joint significance. The left-sided t_{y}-test is for the lagged dependent variable in levels, testing if the coefficient of the error-correction term is negative and statistically significant. Given that the interaction effect of corruption with the lagged dependent variable in levels is found to be positive (see Table 4) we employ a right-sided t_{y}-test for such interaction effect, i.e. testing if the interaction coefficient is positive and statistically significant. Moreover, for significance level 10%, 5% and 1% the simulated critical values for two-sided t-tests for lagged independent variable in levels (t_x-tests) are, respectively, -1.705, -2.029 and -2.715 for the left tail of the statistic and 1.700, 2.034 and 2.652 for the right tail. To economize on space, for t_x-tests we do not report test statistics that are available from the authors upon request.

Table B.2 shows simulated critical values and test statistics of the bounds testing procedure. Columns 2 to 4 report for each test critical values at 10%, 5% and 1% significance level. Columns 5 to 7 show test statistics for Models 1 to 3. The left column in Model 2 and 3 for the t_{y}-test corresponds to the regime "before crisis", while the right column to "during and after crisis". The left-sided t_{y}-test is for the lagged dependent variable in levels, testing if the coefficient of the error-correction term is negative and statistically significant. Given that the interaction effect of

[18] For more details see Pesaran et al. (2001), p. 304.

[19] In Case II ("restricted intercept") the intercept is included in the steady-state relationship, whereas in Case III ("unrestricted intercept") it is not. Alternatively, under the null of no co-integration, the dependent variable in levels in Case II is modelled as a random walk, i.e. $y_{i,t} = y_{i,t-1} + e_{i,t}$, and in Case III as a random walk with drift, i.e. $y_{i,t} = y_{i,t-1} + c + u_{i,t}$.

[20] This is in line with the conservative approach by Shin et al. (2014) for the bounds testing procedure with non-linear ARDLs where they use the initial number of regressors, i.e. prior to their decomposition for the construction of asymmetric variables.

corruption with the lagged dependent variable in levels is found to be positive (see Table 4) we employ a right-sided t_y-test for such interaction effect, i.e. testing if the interaction coefficient is positive and statistically significant.

There is strong evidence of cointegration in Models 1 and 2 given that the null is rejected for all main tests ($F_{y\mathbf{x}}$, t_y, $F_{\mathbf{x}}$) at 1% significance level. For Model 3, the F-tests are passed at 1% level. The right-sided t_y-test for the interaction of error-correction term with corruption is also passed at 1% level for both periods. Furthermore, the left-sided t_y-test for the error-correction term is passed at 1% level "during and after crisis", but only at 10% "before crisis". Overall, this is evidence of a cointegrating relationship between PB and its covariates in Model 3. In Section 4.2 we show that such an equilibrium relationship breaks down "before crisis" for high levels of public sector corruption.[21]

The above procedure is repeated with respect to the extended version of Model 3 that includes a richer lag structure to allow for the possibility of endogenous regressors, as discussed in Appendix A. For this purpose, we derive a new set of sample- and lag-specific critical values using Monte Carlo simulations as previously – i.e. 10,000 replications, $k = 9$ regressors, $N = 77$ cross-sections, $T = 72$ time periods – but this time with the addition of three lags of changes in the dependent variable.

TABLE B.3 Simulated critical values and test statistics of bounds testing procedure for the extended Model 3 with the addition of three lags of changes in the dependent variable

	Simulated critical values for different significance levels			Test statistics of alternative models	
	10%	5%	1%	Extended Model 3	
$F_{y\mathbf{x}}$-test – Case II	1.599	1.826	2.277	16.919	
$F_{y\mathbf{x}}$-test – Case III	1.634	1.862	2.383	17.185	
$F_{\mathbf{x}}$-test – Case II	1.633	1.877	2.386	8.982	
$F_{\mathbf{x}}$-test – Case III	1.671	1.924	2.487	5.978	
left-sided t_y-test	-1.667	-2.008	-2.785	-2.720	-16.386
right-sided t_y-test	1.233	1.593	2.313	2.855	2.139

This table presents simulated critical values for different significance levels and test statistics for the extended Model 3 with three lans of changes in the dependent variable. Bounds testing involves two critical values for given level of statistical significance, i.e. one for $I(0)$ and another for $I(1)$ type of regressors. To be conservative, we consider the highest absolute critical value to avoid overrejection of the null. Columns 2 to 4 report for each test critical values at 10%, 5% and 1% significance level. Column 5 shows test statistics for Model 3. The left column for the t_y-test corresponds to the regime "before crisis", while the right column to "during and after crisis". $F_{y\mathbf{x}}$-test – Case II examines the joint significance of lagged dependent variable in levels, lagged independent variables in levels and the constant term. $F_{y\mathbf{x}}$-test – Case III excludes the constant term from the test of joint significance. The left-sided t_y-test is for the lagged dependent variable in levels, testing if the coefficient of the error-correction term is negative and statistically significant. Given that the interaction effect of corruption with the lagged dependent variable in levels is found to be positive (see Table A1) we employ a right-sided t_y-test for such interaction effect, i.e. testing if the interaction coefficient is positive and statistically significant. Moreover, for significance level 10%, 5% and 1% the simulated critical values for two-sided t-tests for lagged independent variable in levels (t_x-tests) are, respectively, -1.706, -2.037 and -2.691 for the left tail of the statistic and 1.712, 2.059 and 2.729 for the right tail. To economize on space, for t_x-tests we do not report test statistics that are available from the authors upon request.

Table B.3 provides strong evidence of cointegration also for the extended version of Model 3. The F-tests are passed at 1% level, the right-sided t_y-test for the interaction of error-correction term with corruption is also passed at 1% "before crisis" and 5% "during and after crisis", while the left-sided t_y-test for the error-correction term is passed at 5% "before crisis" and at 1% "during and after crisis". Under student-t distribution with five degrees of freedom the bounds testing results remain qualitatively unaltered.

[21] Under a fat-tailed data generating process differences in critical values relative to standard normal turn out to be trivial. Assuming student-t distribution with five degrees of freedom (see, for example, Christopoulos et al. 2021 and Cho et al. 2015) the mean absolute deviation of critical values relative to standard normal are about 1% for each test across significance levels.

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