Banking System Efficiency and Firm Resilience*

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Abstract

Employing a Bayesian principal component analysis, we construct time-varying measures of banking system efficiency. Firms operating in economies with efficient banking systems exhibit greater resilience to economic shocks, as evidenced by their reduced capital investment sensitivity to crises. This mitigating effect is pronounced for firms reliant on bank financing. While efficient banks expand credit during downturns, they preferentially allocate funds to firms with collateralizable assets, potentially neglecting distressed borrowers. Our analysis further reveals that high-performing firms disproportionately benefit from efficient banking systems, while the profitability and value of pre-crisis underperforming firms decline more sharply in economies with higher banking efficiency, suggesting efficiency spillovers to the non-financial sector.

Keywords: banking efficiency, economic crisis, investment, economic recovery

JEL: G21, G31, G15

1. Introduction

The relationship between banking institutions and economic growth has been a subject of intense debate among economists since the seminal work of Bagehot (1873). Financial intermediaries are compensated for providing services to produce, trade, and settle financial contracts that can be used to pool funds, share risks, transfer resources, produce information, and provide incentives (Philippon 2015). Bank financing has been consistently identified as a crucial catalyst for economic expansion, fostering productivity (Bertrand *et al.* 2007; Butler & Cornaggia 2011; Krishnan *et al.* 2014) and growth (King & Levine 1993; Levine & Zervos 1993; Berger & Sedunov 2017). The importance of external financing is amplified during periods of economic turmoil, as evidenced by the heightened vulnerability of firms with weaker balance sheets during the Global Financial Crisis (Campello *et al.* 2010; Duchin *et al.* 2010; Kahle & Stulz 2013; Giroud & Mueller 2017).

While the impact of banking institutions during financial crises has been extensively studied (e.g., Bernanke 1983; Chodorow-Reich 2013; Benmelech *et al.* 2019), the role of banking system efficiency amid non-financial economic crises remains largely unexplored. We fill this gap in the literature by examining the impact of banking efficiency on firm investment and performance amidst an economic crisis.[1] The COVID-19 pandemic presents a unique setting to examine this relationship, as it represents the most recent and significant economic crisis to originate outside the financial sector.[2] With its global reach, unparalleled impact on both developed and developing nations (Ellul *et al.* 2020), and the absence of major banking disruptions (Berger & Demirgüç-Kunt 2021), the pandemic offers a laboratory to evaluate the influence of banking efficiency on firm behavior during economic crises.

A sound banking system is instrumental in channeling savings towards productive investments, thereby fostering economic growth (Barth *et al.* 2009).[3] A Prior research has emphasized the critical role of efficient financial intermediation in facilitating this process (Jayaratne & Strahan 1998; Cihak *et al.* 2012). By effectively allocating capital to the private sector, efficient banking systems enhance both bank intermediation and managerial productivity. Building upon the theoretical frameworks of Boyd and de Nicoló (2005) and

[1] The efficiency of financial institutions is assessed through their ability and impact on lending to corporations. A more efficient banking sector translates to lower intermediation costs for non-financial firms, facilitating access to capital and potentially stimulating growth. This metric differs from the total factor productivity of individual banks, which focuses solely on their internal resource utilization.

[2] Non-financial economic crises are economic downturns that did not originate within the financial sector of the economy.

[3] The association between banking efficiency and economic growth is well-established, with numerous studies – including those by Jayaratne and Strahan (1996), Levine (1998, 1999), and Kroszner and Strahan (2014) – highlighting its crucial role.

Corbae and Levine (2018), we present a simple model of an efficient banking sector that is characterized by intense competition, minimal agency costs, and consequently, narrow interest margins and low operating expenses. Such a system optimizes resource allocation by extending credit to firms at a low intermediary cost while operating within a competitive environment.

Despite the critical role of banking efficiency in economic performance, the relationship between banking system efficiency (henceforth, BSE) and corporate behavior during economic downturns remains largely unexplored. A primary obstacle to empirical investigation in this area is the absence of a comprehensive, consistently measured, and time-varying cross-country BSE indicator.[4] Existing proxies, such as industry concentration, are problematic due to their endogenous nature and dependence on market definition (Carlson *et al.* 2022). Moreover, relying on changes in branching restrictions to assess BSE is hindered by confounding factors, including banks' diversification capabilities (Goetz *et al.* 2016) and the interplay of bank mergers and political-economic forces (Agarwal *et al.* 2012; Calomiris & Haber 2015).

To address this concern, we propose a data driven approach to measure BSE. Employing machine learning, we extract the systematic component underlying efficiency-related characteristics. Specifically, we utilize Bayesian Principal Component Analysis (B-PCA) to handle missing data, a prevalent issue in international financial development datasets. Unlike standard PCA, B-PCA simultaneously imputes missing values and estimates model parameters, mitigating potential biases (Bishop 1998; Tipping & Bishop 1999; Minka 2000; Oba *et al.* 2003). Our baseline B-PCA incorporates net interest margin, lending minus deposits spread, bank overhead costs to total assets, non-interest income to total income, and return on assets (ROA) as input variables. Employing data from over 150 countries and a five-year rolling window, we calculate the first principal component as our novel country-level BSE index, with weights dynamically adjusted to prevent look-ahead bias.[5]

We rigorously assessed the BSE index's robustness and predictive power. Through simulations involving random data removal, we confirmed the index's resilience to data scarcity, maintaining a correlation above 97% with the standard PCA's first component even with 15% data loss. To evaluate predictive ability, we compared the BSE index to the IMF's Financial Institution Efficiency (FIE) index. Out-of-sample analysis revealed that the BSE

[4] While a few studies have endeavored to establish country-level indexes of financial development (Sahay *et al.* 2015; Svirydzenka 2016), these existing indexes are subject to biases arising from subjective handling of missing variables, look-ahead bias, and non-transparent weighting of financial characteristics.
[5] We find similar results when the sample of countries in the Bayesian PCA is limited to countries listed on the Compustat Global universe.

index consistently outperformed the FIE index in terms of correlation and R^2 when predicting future banking characteristics, demonstrating its superior ability to forecast performance.

Our primary hypothesis posits that firms operating within economies characterized by efficient banking systems exhibit reduced vulnerability to economic downturns. This resilience is attributed to the critical role of banks as a vital source of corporate financing during periods of economic stress. As highlighted by Caballero and Krishnamurthy (2001), robust financial systems mitigate firm cash flow constraints and influence the cyclical nature of investment (Aghion *et al.* 2010). Disruptions in bank credit channels during economic turbulence can amplify contractionary pressures on firm investment (Kroszner *et al.* 2007; Kroszner & Strahan 2014). The COVID-19 pandemic serves as a stark illustration of this phenomenon, with banks facing an unprecedented surge in liquidity demand (Li *et al.* 2020).[6] We contend that efficient banking institutions act as a safety net for corporations, attenuating the adverse consequences of crises on investment.

To empirically test our hypothesis, we analyze a representative sample of publicly traded companies across 55 global markets. A dummy variable, equaling zero for the pre-crisis period (2012-2019) and one for the post-crisis period (2020-2021), captures the impact of the COVID-19 crisis. To assess the role of banking efficiency during this period, we introduce an interaction term between the BSE index and the crisis dummy.[7] Our findings reveal a significant positive interaction effect, supporting the hypothesis that the decline in firm investment during economic crises is less pronounced in economies with efficient banking systems compared to those with inefficient ones. A one standard deviation increase in the BSE index is associated with approximately a 5.7% reduction in the crisis impact on firm-level capital investment (relative to the average). Notably, our results remain robust after controlling for additional macroeconomic factors, including interest and inflation rates, unemployment, stock market and corporate bond market development, and banking regulatory capital.

To address potential reverse causality, we employ a two-stage instrumental variable approach using legal origin. Building upon previous research (Levine 1999; Levine *et al.* 2000), we leverage the historical influence of legal systems on banking development as an exogenous factor. As legal origin shapes banking without directly affecting investment growth, instrumenting with legal origin provides strong evidence against reverse causality (La Porta *et*

[6] Although banks typically display procyclical lending behavior, they remain the main source of liquidity for most firms (Acharya & Steffen 2020). Using BIS data, we confirm that countries with efficient banking institutions provided a higher volume of credit to the private non-financial sector during the COVID-19 crisis.
[7] This empirical framework enables us to include both time-varying country and firm characteristics as well as firm and time-fixed effects.

al. 1998). Utilizing fitted values of the BSE index, we confirm a robust link between banking efficiency and firm investment during the crisis period.

To further mitigate concerns about omitted variable bias, we examine the interaction effect between banking efficiency and sector-level external financing dependence, following Rajan and Zingales (1998). By analyzing differential post-crisis investment changes across sectors with varying levels of pre-crisis bank dependence, we isolate the causal impact of banking efficiency on firm investment. Our findings indicate that the positive effect of banking efficiency on investment is concentrated in sectors with higher external financing needs, providing additional support for the causal relationship.[8] We corroborate these results using the bank dependence measure proposed by Bertrand *et al.* (2007).

Having established a causal relationship between BSE and firm investment, we investigate whether efficient banks prioritize lending to firms based on financing ability (tangible assets) or financing need (financial constraints) during economic crises. To identify firms with greater financing capacity, we employ two well-established proxies: the tangible asset ratio and the cyclicality of durable goods industry sales. Lower tangibility restricts credit access due to limited collateral (Berger *et al.* 1996; Kroszner *et al.* 2007). Additionally, adverse demand shocks in durable goods industries can reduce asset exchangeability, effectively lowering tangibility (Almeida & Campello 2007). To capture financial constraints, we utilize firm cash holdings and the sensitivity of cash flow to changes in cash holdings. Firms facing financial constraints tend to accumulate cash reserves and exhibit heightened cash flow sensitivity (e.g., Kim *et al.* 1998; Opler *et al.* 1999; Almeida *et al.* 2004; Erel *et al.* 2015). Our findings indicate that the positive impact of BSE on investment is amplified for firms with higher tangible assets and those operating in non-durable goods sectors. Conversely, we find no evidence that efficient banks prioritize lending to financially constrained firms during downturns, suggesting potential disciplining effects of banking efficiency.

We further examine the disciplining role of BSE for the real economy. Our results show a pronounced decline in profitability (ROA) and firm value (Tobin's *Q*) for pre-crisis underperforming firms in economies with higher BSE. This suggests that efficient banks adopt more prudent lending practices during crises. These findings provide compelling evidence that sound banking systems enforce stricter lending standards, contributing to improved allocative efficiency among non-financial firms.

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[8] Similar to banking crises (Kroszner *et al.* 2007; Dell'Ariccia *et al.* 2008), we also find that the investment growth in externally dependent sectors is lower during economic crises regardless of the level of banking efficiency.

This paper examines the relationship between financial slack and the propagation of economic shocks, extending existing research. Previous studies have shown that firms with weaker balance sheets were disproportionately affected by the Global Financial Crisis (GFC) (Duchin *et al.* 2010; Kahle & Stulz 2013; Giroud & Mueller 2017). Firm performance sensitivity to financial crises is contingent on credit constraints (Campello *et al.* 2010). Moreover, the ability to issue low-cost equity mitigates the negative impacts of banking crises (Levine et al., 2016). Recent evidence suggests that firms with greater financial flexibility better navigated the revenue shortfalls during the COVID-19 shock (Fahlenbrach *et al.* 2021; Barry *et al.* 2022). Our study contributes by demonstrating that firms in countries with robust banking systems experienced less severe declines in capital investment during the crisis.

Our research also contributes to the growing literature on the real effects of banking sector quality (e.g., Jayaratne & Strahan 1996, 1998; Black & Strahan 2002; Ivashina & Scharfstein 2010). While increased bank concentration hinders credit access for new and young firms (Cetorelli 2003; Beck *et al.* 2004; Bonaccorsi di Patti & Dell'Ariccia 2004), banking competition is associated with smaller firm size (Cetorelli & Strahan 2006). Bertrand *et al.* (2007) find that banking deregulation reduced bank bailouts of struggling firms. Carlson *et al.* (2022) link lower credit provision by national banks to decreased economic activity. Our study extends this research by demonstrating that efficient banks reduce lending to underperforming firms during crises, enhancing overall allocative efficiency in the non-financial sector.

Finally, our study contributes to the literature on cross-country banking efficiency. While previous studies have used banking inputs and outputs to calculate efficiency scores, they often focus on developed nations and are sensitive to model specification (e.g., Berg *et al.* 1993; Allen & Rai 1996; Pastor *et al.* 1997; Maudos *et al.* 2002; Kwan 2003). Cihak *et al.* (2012) proposed cross-country crude variables for banking efficiency. We advance this by constructing cross-country time-varying efficiency indexes using Bayesian PCA on these variables, covering over 150 countries.

The paper proceeds as follows. Section 2 outlines the study's hypotheses. Section 3 develops the theoretical framework and empirical methodology for constructing the BSE index. Section 4 introduces the novel BSE indexes. Section 5 examines the impact of BSE on firm investment. Section 6 examines the prioritization of bank loan allocation in high BSE economies. Section 7 analyzes the impact of BSE for the non-financial firm restructuring activities, and Section 8 concludes.

2. Hypothesis Development

2.1. Sensitivity of Investment to Economic Crises

Abrupt contractions in bank credit availability can severely impact economic activity, dampening firm investment and employment (e.g., Kroszner *et al.* 2007; Chodorow-Reich 2013; Kroszner & Strahan 2014; Benmelech *et al.* 2019). Conversely, access to finance can help firms navigate economic downturns (Fahlenbrach *et al.* 2021; Barry *et al.* 2022).

Access to low-cost bank credit is crucial for firms during economic crises, as it is a primary source of external financing. Building on this premise, we propose the following hypothesis:

Hypothesis 1: *Firms in economies with efficient banking systems exhibit lower sensitivity of capital investment to economic crises.*

We posit that firms operating in economies with higher banking system efficiency are more resilient to economic downturns, resulting in a reduced sensitivity of investment to economic fluctuations. In contrast, firms in economies with inefficient banking systems are more vulnerable to the adverse effects of economic crises, leading to a heightened sensitivity of investment to economic shocks.

2.2. The Role of Collateral Assets

Our second hypothesis posits that efficient banks prioritize lending to firms with the capacity to repay loans rather than those facing financial constraints during economic crises. This aligns with research emphasizing the role of collateral assets in shaping firms' investment decisions (Gan 2007; Chaney *et al.* 2012). Collateral mitigates information asymmetries between firms and lenders, reducing adverse selection and credit rationing (Stiglitz & Weiss 1981). Additionally, collateral addresses moral hazard concerns (Boot *et al.* 1991; Aghion & Bolton 1997; Holmstrom & Tirole 1997) and contractual enforcement challenges (Albuquerque & Hopenhayn 2004; Cooley *et al.* 2004).

As a prerequisite for securing bank loans, firms must pledge tangible assets as collateral (Hart & Moore 1994; Kiyotaki & Moore 1997). Tangible asset values serve as a pivotal determinant in expanding debt capacity and facilitating investment. Firms with higher intangible assets face greater financing challenges (Kroszner *et al.* 2007). Collateral-rich firms, with better loan renegotiation capabilities, are more resilient to economic crises. Based on this, we propose the following hypothesis:

Hypothesis 2: *The impact of banking efficiency on investment is amplified for firms with higher collateral assets during crises.*

2.3. Stricter Lending Practices and Allocative Efficiency

Our third hypothesis examines the impact of stricter lending practices on allocative efficiency within the non-financial sector during crises. Research suggests that banking sector competition improves access to credit for non-financial firms (Cetorelli 2003; Beck *et al.* 2004; Bonaccorsi di Patti & Dell'Ariccia 2004). Less competitive markets often lead to risk-averse banks prioritizing loan security due to reduced market pressure and increased customer scrutiny (Carlson *et al.* 2022).

Credit growth demonstrably influences real economic outcomes (King & Levine 1993; Levine & Zervos 1998; Chodorow-Reich 2013; Benmelech *et al.* 2019). Bertrand *et al.* (2007) finds that efficient banks are less likely to lend to underperforming firms, leading to a wider profitability gap between high and low-performing firms. Furthermore, utilizing historical data from the US National Banking Era, Carlson *et al.* (2022) identify a decrease in per capita manufacturing capital investment within markets characterized by low banking competition.

Based on the established relationship between efficient banking systems and real economic outcomes, we propose the following hypothesis:

Hypothesis 3: *The profitability and firm value gap between high and low-performing firms should widen in countries with more efficient banking systems.*

3. Banking System Efficiency: Theoretical Motivation and Methodology

To ground our measure of banking system efficiency, we develop a simplified model of a representative banking sector. This model helps identify observable characteristics associated with a sound banking system. Subsequently, we propose a systematic approach to constructing country-level efficiency indexes using these characteristics.

3.1. A Model of the Banking Sector

Drawing on Boyd and de Nicoló (2005) and Corbae and Levine (2018), we model the banking sector, focusing on the sector itself rather than general equilibrium outcomes. Our model also incorporates managerial rent extraction.

3.1.1. *Banking Environment*

We assume a decentralized economy with N banks competing for insured deposits in a Cournot fashion. The total supply of deposits is represented by an upward sloping inverse supply curve given by $Z = \sum_{i=1}^{N} D_i$. We assume that the rate of interest (r_D) on deposits is a function of total deposits (Z). The inverse deposit supply function is given by $r_D(Z) = \gamma Z$.

The bank intermediates each unit input for a payoff of $A \cdot S$ units of goods with probability $p(S)$ and 0 otherwise. The variable S represents the riskiness of the portfolio. The bank's strategy exhibits a risk-return trade-off where higher returns are associated with lower success probabilities. Following Corbae and Levine (2018), we use assume that $p(S) = 1 - S^2$. Hence, $p'(S) = -2S < 0$. The term A represents the firm's total factor productivity.

3.1.2. *Bank's Optimization Problem*

The bank manager's optimization problem is to choose (S_i, D_i) each period to maximize the profits subject to a leverage constraint $\frac{D_i}{E_i} = \lambda$. Bank i's static profit function is:

$$\pi_i(N) = p(S_i)\underbrace{[A \cdot S_i - (r_D(Z) + \alpha)]}_{\substack{interest\\margin}} D_i + p(S_i)\underbrace{\phi_D(Z)}_{\substack{rent\\extration}} D_i. \qquad ...(1)$$

The variable $\phi_D(Z)$ represents the managerial rent extraction and α is the deposit insurance. Based on Bebchuk *et al.* (2002), we assume that managerial rent extraction will not cause the bank executives harm if it can be packaged or hidden within operational costs, evading regulatory scrutiny. The parameter can also be interpreted as bank managers attempt to convince the market of its credit evaluation abilities. They may conceal the extent of bad loans by adopting a liberal credit policy that generates up-front fees at the expense of future credit quality (Rajan 1994). The dynamic problem of bank i is given by:

$$V_i(N) \equiv \max_{S_i, D_i} \quad \pi_i(N) + \beta\, p(S_i) V_i(N'), \qquad ...(2)$$

subject to $\frac{D_i}{E_i} = \lambda$, where N' denotes the number of banks next period. Note that $R_i \equiv A \cdot S_i - (r_D(Z) + \alpha)$ denotes the bank's interest margin. The incumbent bank maximizes the present discounted value of profits by Cournot competing with the other $N - 1$ incumbent banks for their deposits at rate $r_D(Z)$.

The shareholders can only make an initial equity injection E_i to pay for the entry cost κ to start new bank. This implies that shareholders with discount rate δ will inject equity to fund bank *i* entry provided:

$$E_i(N) \equiv \frac{\pi_i(N)}{1-\delta\, p(S_i)} \geq \kappa. \qquad \ldots(3)$$

In a symmetric equilibrium, the value of the bank is:

$$V(N) \equiv \frac{[1-\delta\, p(S)]}{[1-\beta\, p(S)]} E(N), \qquad \ldots(4)$$

where $\omega(S) \equiv \frac{[1-\delta\, p(S)]}{[1-\beta\, p(S)]}$ is the wedge between managerial value of the firm and shareholder value. In the case of bank managers with short-term goals, the wedge $\omega(S) < 1$. An increase in principle-agent conflict reduces the β further deviating $\omega(S)$ from unity.

The first order conditions (FOCs) are reported in the Appendix for brevity. In an equilibrium where the leverage requirement is binding, the FOC equations can be written as:

$$p(S_N) = \frac{p'(S_i)}{A}\left[R_N + \phi_D(Z) + \beta\, \frac{E(N)}{D_N}\ \omega(S_N)\right]. \qquad \ldots(5)$$

$$R_N + \phi_D(Z) = \frac{r_D'(Z)N_N}{N_N} - \frac{\phi_D'(Z)Z_N}{N_N} + \frac{\mu}{p(S_i)\,\kappa}\,. \qquad \ldots(6)$$

3.1.3. Banking System Efficiency

An efficient banking system should be characterized by higher *competition* and lower *agency conflicts* (i.e., banks managers should align their long-term objectives with shareholder interests rather than prioritizing short-term profits).

In the equilibrium, competition and interest margin are negatively correlated. As competition intensifies, a bank's interest margin decreases:

$$\frac{\partial R_N}{\partial N} = -\frac{r_D'(Z)Z_N}{{N_N}^2} + \frac{\phi_D'(Z)Z_N}{{N_N}^2} < 0. \qquad \ldots(7)$$

Similarly, managerial rent extraction (ϕ_D) and profits ($\pi_i(N)$) decrease with increased competition: $\frac{\partial \phi_D}{\partial N} < 0$ and $\frac{\partial \pi_i(N)}{\partial N} < 0$.

In the equilibrium, agency conflicts and managerial rent extraction are negatively correlated. As agency conflicts diminish, managerial rent extraction also decreases:

$$\frac{\partial \phi_D}{\partial \omega} = -\beta \frac{E(N)}{D_N} < 0. \qquad \text{...(8)}$$

Conversely, as bank managers become more myopic, managerial rent extraction increases. Without effective governance and regulation, bank managers may prioritize increasing interest margins and managerial rents to enhance short-term survival probabilities $\left(\frac{\partial p(S_N)}{\partial R_N} > 0 \text{ and } \frac{\partial p(S_N)}{\partial \phi_D} > 0\right)$.

Our simplified model identifies key characteristics of an efficient banking environment: (1) lower interest margins and (2) lower managerial rent extraction (potentially disguised as overhead costs).

3.2. Empirical Estimation: Machine Learning

Using the insights from the model, we propose a systematic approach to constructing country-level indexes of efficiency in the banking system. While principal component analysis (PCA) is a prevalent technique for extracting latent factors, its standard application necessitates a complete set of observed data. However, the reality is that banking characteristics often exhibit missing or unobserved values for certain country-years. To address this challenge, we opt for a probabilistic PCA, drawing upon advancements in the machine learning literature (Bishop 1998; Tipping & Bishop 1999; Minka 2000; Oba *et al.* 2003).

Our estimation method consists of three elementary processes: (1) the principal component (PC) regression, (2) Bayesian estimation, and (3) the variational Bayes (VB) repetitive algorithm.[9]

3.2.1. Probabilistic Principal Component Analysis

In the absence of missing data, a conventional PCA can be used to reduce the dimensionality of a large dataset. Consider the $D \times N$ matrix $\mathbf{Y}$ which represents the dataset of banking efficiency characteristics related to interest margin and managerial rent extraction, where D is the number of characteristics and N is the number of economies. The (i, j)

[9] The algorithm is similar in sprit to expectation–maximization (EM) algorithm.

component of the matrix $y_{i,j}$ denote the j^{th} characteristic in i^{th} market. The conventional PCA is obtained by computing the sample covariance matrix for the vector y_i is given by:

$$\boldsymbol{S} = \frac{1}{N}\sum_{l=1}^{N}(y_i - \boldsymbol{\mu})(y_i - \boldsymbol{\mu})^T,$$

where $1 \leq i \leq N$ and $\boldsymbol{\mu} = \frac{1}{N}\ \sum_{i=1}^{N} y_i$, which is the mean vector of $\boldsymbol{y}$. The eigenvectors u_i and eigenvalues λ_i of $\boldsymbol{S}$ are computed, where $\boldsymbol{S}u_i = \lambda_i u_i$ and $i = 1, \dots, D$. The l^{th} principal axis vector is given by $\boldsymbol{\omega_l} = \sqrt{\lambda_l} u_l$ and l^{th} factor score for vector $\boldsymbol{y}$ is given by $x_l = \left(\frac{\boldsymbol{\omega_l}}{\lambda_l}\right)^T\ \boldsymbol{y}$.

While conventional PCA lacks an explicit probabilistic interpretation, Tipping and Bishop (1999) demonstrated its equivalence to the maximum likelihood solution of a specific latent variable model. We can introduce a k-dimensional latent variable $\boldsymbol{\omega}$ whose prior distribution is a zero mean Gaussian $p(\boldsymbol{\omega}) = \mathcal{N}(0,\ I_K)$ and I_K is a unit matrix. The observed variable $\boldsymbol{y}$ can be defined as a linear transformation of $\boldsymbol{\omega}$ with additive Gaussian noise:

$$\boldsymbol{y} = \sum_{l=1}^{K} x_l \boldsymbol{\omega_l} + \varepsilon. \tag{9}$$

The probabilistic PCA model postulates that the residual error term ε and the factor scores x_l, $1 \leq l \leq K$ in equation (1), adhere to Gaussian distributions:

$$p(\boldsymbol{x}) = \mathcal{N}(x|0,\ I_K),$$
$$p(\varepsilon) = \mathcal{N}(\varepsilon|0, (1/\tau)\ I_D),$$

where $\mathcal{N}(x|\mu,\ \Sigma)$ denotes a Gaussian distribution for x with mean and covariance μ and Σ, respectively. I_K is a $K\ \times\ K$ identity matrix and τ is a scalar inverse variance of ε. This implies that $p(\boldsymbol{y}_i|\boldsymbol{\omega_l}) = \mathcal{N}(x_l\boldsymbol{\omega_l}, (1/\tau)\ I_D)$.

3.2.2. Missing Data

In our country level banking dataset $\mathbf{Y}$, where a subset of values, denoted as $\boldsymbol{y^{miss}}$, is absent. PC regression aims to estimate these missing values by leveraging the observed portion of the dataset, $\boldsymbol{y}^{obs}$. Let $\boldsymbol{\omega_l}^{obs}$ and $\boldsymbol{\omega_l}^{miss}$ denote the observed and missing parts of each principal axis $\boldsymbol{\omega_l}$. The factor scores for the vector $\boldsymbol{y}$, represented by $\boldsymbol{x}$, are obtained by minimizing the error:

$$err = \|\boldsymbol{y}^{obs} - \boldsymbol{W}^{obs}\boldsymbol{x}\|^2,$$

where $\boldsymbol{W}^{obs}$ denotes the matrix with column vectors $\boldsymbol{\omega_1}^{obs}, \dots, \boldsymbol{\omega_K}^{obs}$. The least-square solution is given by:

$$\boldsymbol{x} = \left(\boldsymbol{W}^{obs^{\boldsymbol{T}}}\boldsymbol{W}^{obs}\right)^{-\boldsymbol{1}}\boldsymbol{W}^{obs^{\boldsymbol{T}}}\boldsymbol{y}^{obs}.$$

The estimated missing values can then be recovered using the relationship:

$$\boldsymbol{y}^{miss} = \boldsymbol{W}^{miss}\boldsymbol{x}. \tag{10}$$

However, to implement this imputation procedure, the complete matrix $\boldsymbol{W}$, encompassing both $\boldsymbol{W}^{obs}$ and $\boldsymbol{W}^{miss}$, is required.

3.2.3. Bayesian Estimation

In line with the established literature, we adopt a Bayesian treatment to probabilistic principal component analysis (Bishop 1999; Oba *et al.* 2003). This involves employing Bayes theorem to estimate the posterior distributions of $\boldsymbol{X}$ and the model parameters ($\boldsymbol{\theta}$). We estimate the posterior distribution of $\boldsymbol{\theta}$ and $\boldsymbol{X}$ according to the Bayes theorem:

$$p(\boldsymbol{\theta}, \boldsymbol{X}|\boldsymbol{Y}) \propto p(\boldsymbol{Y}, \boldsymbol{X}|\boldsymbol{\theta})\, p(\boldsymbol{\theta}). \tag{11}$$

To begin our analysis, we introduce a prior distribution $P(\boldsymbol{W}, \boldsymbol{\mu}, \tau)$ over the model's parameters. The corresponding posterior distribution $P(\boldsymbol{W}, \boldsymbol{\mu}, \tau|\mathbf{Y})$ is then obtained by Bayes theorem, which involves multiplying the prior distribution by the likelihood function given by:

$$\ln p(\,\boldsymbol{y} \mid \boldsymbol{\theta}) = -\frac{\tau}{2}\|\boldsymbol{y} - \boldsymbol{W}\boldsymbol{x} - \boldsymbol{\mu}\|^2 - \frac{\tau}{2}\|\boldsymbol{x}\|^2 + \frac{D}{2}\ln\tau + \frac{K+D}{2}\ln 2\pi, \tag{12}$$

where $\boldsymbol{\theta} \equiv \{\boldsymbol{W}, \boldsymbol{\mu}, \tau\}$ is the parameter set.

To implement this framework, we need to define the prior distribution and the formulation of a tractable algorithm. Following Oba *et al.* (2003), we assume conjugate priors for τ and $\boldsymbol{\mu}$, and a hierarchical prior for $\boldsymbol{W}$, which is $p(\boldsymbol{W}|\tau, \alpha)$ that is parameterized by a hyperparameter $\alpha \in \mathbb{R}^K$. For brevity, we report the definition of priors in the Appendix. Please refer to Oba *et al.* (2003) for a detailed analysis.

The posterior of the missing values is $q\left(\boldsymbol{Y}^{miss}\right) = p\left(\boldsymbol{Y}^{miss}|\boldsymbol{Y}^{obs}, \boldsymbol{\theta}_{\boldsymbol{true}}\right)$, where $\boldsymbol{\theta}_{\boldsymbol{true}}$ is the true parameter set and $\boldsymbol{Y}^{obs}$ is the observed values. The posterior given the $\boldsymbol{\theta}_{\boldsymbol{true}}$ is equivalent to the PC regression in (2). Given the posterior $q(\boldsymbol{\theta})$ instead of the true parameter $\boldsymbol{\theta}_{\boldsymbol{true}}$, the posterior distribution of the missing values is given by:

$$q\left(\boldsymbol{Y}^{miss}\right) = \int p\left(\boldsymbol{Y}^{miss}|\boldsymbol{Y}^{obs}, \boldsymbol{\theta}\right) q(\boldsymbol{\theta}) d\boldsymbol{\theta},$$

which corresponds to the Bayesian PC regression. We require $\boldsymbol{Y} = \left(\boldsymbol{Y}^{obs}, \boldsymbol{Y}^{miss}\right)$ to estimate the posterior $q(\boldsymbol{\theta}) = p(\boldsymbol{\theta}|\boldsymbol{Y}, \boldsymbol{\alpha}_{ML-II})$ and $q(\boldsymbol{\theta})$ to estimate the posterior $q\left(\boldsymbol{Y}^{miss}\right) = \int p\left(\boldsymbol{Y}^{miss}|\boldsymbol{Y}^{obs}, \boldsymbol{\theta}\right) q(\boldsymbol{\theta}) d\boldsymbol{\theta}$. Hence, we are required to obtain $q(\boldsymbol{\theta})$ and $q\left(\boldsymbol{Y}^{miss}\right)$ simultaneously.

Employing an iterative algorithm, we derive the posterior distributions $q(\boldsymbol{\theta})$ and $q\left(\boldsymbol{y}^{miss}\right)$. In accordance with the methodologies proposed by Attias (1999) and Sato (2001), we utilize the Variational Bayes (VB) algorithm for Bayesian estimation of the posterior distributions $q(\boldsymbol{\theta})$ and $q\left(\boldsymbol{y}^{miss}\right)$. The VB algorithm is explained in the Appendix.

Utilizing the VB algorithm, we compute the posterior distributions $q(\boldsymbol{\theta})$ and $q\left(\boldsymbol{y}^{miss}\right)$, which converge to the global optima. The missing values in the expression matrix are imputed to the expectation for the estimated posterior distribution: $\widehat{\boldsymbol{Y}^{miss}} = \int \boldsymbol{Y}^{miss}\ q\left(\boldsymbol{Y}^{miss}\right)\ d\boldsymbol{Y}^{miss}$.

4. Banking System Efficiency (BSE) Index

4.1. Banking Data

We employ three proxies related to interest margin: the lending minus deposit spread , net interest margin (NIM), and return on assets (ROA). To proxy managerial rent extractions, we employ overhead costs as a percentage of total assets and non-interest income to total income ratio.[10] We utilize the World Bank Group's Global Financial Development Database to gather these banking characteristics because employing a single data source for all countries enables seamless cross-market index comparisons.

The net interest margin represents the accounting value of a financial institution's net interest revenue as a proportion of its average interest-bearing assets. The lending-deposit

[10] A larger share of noninterest income in the form of fees, commissions, and trading can increase potential agency problems that arise within institutions as they become larger (Jensen & Meckling 1976; Jensen 1986). It may also increase opportunities for bank managers to trade against the bank's interest (Myers & Rajan 1998) and increase the overall bank risk (Demirgüç-Kunt & Huizinga 2010).

spread reflects the difference between lending and deposit rates. The lending rate denotes the rate charged by banks on loans to the private sector, while the deposit interest rate represents the rate offered by commercial banks on three-month deposits. Bank non-interest income to total income signifies the income generated from non-interest-related activities such as net gains on trading and derivatives, net gains on other securities, net fees, and commissions as a percentage of total income (net-interest income plus noninterest income). The overhead cost to total assets ratio represents a bank's operating expenses as a proportion of the value of all assets held. The ROA metric captures commercial banks' after-tax net income to yearly averaged total assets.

4.2. Index Construction

For our baseline index construction, we employ the five banking characteristics: NIM, lending-deposits spread, ROA, overhead costs as a percentage of total assets, and non-interest income to total income ratio. To circumvent look-ahead bias, we utilize the past five years of data to estimate the parameters. Consequently, the weights are adjusted on a rolling basis in our setting.

The first Bayesian principal component (B-PC1) exhibits negative loadings on four out of five banking institutions' efficiency inputs, indicating an inverse relationship between B-PC1 and the raw characteristics of NIM, lending-deposit spread, overhead costs to total assets, and ROA. The loadings on NIM, overhead costs, and ROA are significantly larger, highlighting the importance of these inputs for banking system efficiency.[11] On average, B-PC1 captures approximately 45% of the variation in the B-PCA inputs. We adopt B-PC1 as our measure of BSE. For recent years, we are able to construct the index for over 150 countries.

4.3. Cross-Country Differences in Banking System Efficiency

The BSE index reveals striking heterogeneity in banking efficiency across countries, even within geographically proximate regions.[12] Western Europe generally boasts highly functional banking systems, while those in South America and Africa tend to lag behind in efficiency. Interestingly, both developed and emerging markets are represented in both the high- and low-BSE groups. High-income countries with consistently high BSE index scores

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[11] Figure A1 in the Appendix depicts the B-PC1 plotted against the second principal component (B-PC2). The negative association between the banking characteristics and the first principal component implies that higher values of B-PC1 are associated with sound banking systems.

[12] For a visual, Figure A2 in the Appendix plots a world map with the BSE Indexes using average over 2011 to 2019 (pre-COVID-19 crisis). The darker colors indicate countries with higher BSE scores.

include Japan, France, Belgium, Denmark, Finland, and Luxembourg. Among low-income countries, Lebanon, Vietnam, India, Syria, Morocco, and Tunisia consistently exhibit generally high BSE scores.

The BSE index for the US falls near the median for high-income countries. This finding aligns with earlier studies on banking efficiency, which suggest that US banks are relatively inefficient compared to their global counterparts (Fecher & Pestieau 1993; Pastor *et al.* 1997).

[Please Insert Figure 1 Here]

4.4. Validating the Measure

4.4.1. Simulation-Based Validation

The inherent latent nature of banking system efficiency precludes the construction of an entirely uncontested proxy for this multifaceted concept. Consequently, we adopt a pragmatic approach that prioritizes transparency and systematicity in the development of our banking efficiency indexes.

To assess the accuracy of the newly proposed Bayesian PCA approach in estimating the true index of efficiency in banking systems, we conduct a comprehensive simulation-based validation exercise. This simulation aims to evaluate how closely our BSE index aligns with a true index that would be constructed if we had access to a complete dataset with no missing observations.

We use the observed dataset $\boldsymbol{y}^{obs}$ comprising the raw banking efficiency characteristics of NIM, lending-minus-deposits spread, non-interest income to total income, overhead costs to total assets, and ROA. The simulation procedure involves the following steps:

1. *True Index Estimation:* We estimate the first principal component using the standard PCA, which serves as the true index for the sample $\boldsymbol{y}^{obs}$.

2. *Missing Data Introduction:* We randomly remove a specified percentage of observations from the dataset, simulating varying levels of missing data.

3. *BSE Index Estimation:* For each missing data scenario, we apply the Bayesian PCA method to the incomplete dataset and calculate the corresponding BSE index.

4. *Correlation Analysis:* We compute the correlation coefficient between the BSE index and the “true” index derived from the complete dataset.

This simulation process is repeated 1000 iterations for each level of missing data (ranging from 5% to 15%) to ensure the robustness of our results.

Table 1 Panel A presents the mean and 95% confidence interval for the correlation between the BSE index and the true index across all simulation runs. The average correlation monotonically decrease as the percentage of missing values increases. Intuitively, a higher proportion of missing data limits the information available for the BSE index to accurately capture the underlying true index. Nevertheless, even with 15% missing data, the correlation remains substantial, exceeding 0.97. This demonstrates the robustness of our proposed method under varying levels of missing data, highlighting its potential as a reliable tool for economic analysis in the presence of incomplete information.

4.4.2. Out-of-Sample Analysis: A Comparative Assessment with IMF Indexes

To evaluate the out-of-sample predictive power of the BSE index relative to the IMF's financial institutions efficiency index (FIE), we conduct a comparative analysis of their correlations with raw banking characteristics. This comparison is performed using data from 2018, 2019, and 2020.

We employ indexes constructed solely with data up to 2017. Since we use a rolling window estimation, the 2017 BSE index utilizes information only up to 2017. Conversely, the IMF's index is constructed using the entirety of the available data. For the out-of-sample tests, we utilize the IMF's FIE index published in 2017 based on data up to 2017.

Table 1, Panel B, demonstrates the BSE index's significantly higher R^2 values across all characteristics compared to the IMF's FIE index. For instance, the 2017 BSE index's R^2 with 2018 NIM is 0.90 versus 0.49 for the IMF's index. This outperformance persists in later years, indicating superior capture of out-of-sample dynamics. Overall, the BSE index demonstrates a considerably better out-of-sample fit with key banking metrics.[13]

[Please Insert Table 1 Here]

5. Banking System Efficiency and Firm Investment

Employing BSE indexes, we conduct an examination of the hypothesized relationship between the efficiency in a country's banking system and firm investment behavior during an economic crisis.

[13] Figure A3 in the Appendix depicts the correlation between the 2017 indexes and raw banking characteristics for varying income levels in 2018, 2019, and 2020. Additionally, R^2, the coefficient of determination, is reported for each test.

5.1. Financial Data

We acquire firm-level yearly financial data from the Compustat Global database, excluding financial firms (SIC industry codes between 6000 and 6999), firm-year observations with a non-positive book value of total assets or book value of common equity, and those with missing data. All accounting figures are denominated in US dollars.

Capital investment is the ratio of annual capital expenditure to the book value of total assets at the beginning of the fiscal year. Cash flow to assets is the ratio of annual cash flows to the book value of total assets at the beginning of the fiscal year. Ln Mkt Cap is the market capitalization in the natural logarithm at the end of the fiscal year. Tobin's Q is the ratio of the book value of assets plus the market value of common equity minus the book value of common equity and deferred taxes to the book value of assets as measured at the end of the fiscal year. Leverage is the ratio of the book value of debt divided by the book value of total assets at the beginning of the fiscal year.[14]

5.2. Sample Statistics

Table 2 presents a summary of the key statistics for our cross-national dataset, encompassing 55 economies sampled between 2011 and 2021. All financial variables are winsorized at the 1st and 99th percentile levels to mitigate the impact of outliers.

BSE Index remains stable for most economies over the sample period. Notably, total investment and capital expenditures experienced a discernible decline in most countries during the COVID-19 crisis in 2020 and 2021. However, this decline is observably less pronounced in economies characterized by a higher BSE index.

[Please Insert Table 2 Here]

5.3. Banking System Efficiency and Capital Investments

To examine the relationship between banking system efficiency and capital investment, we estimate the following model:

$$Inv_{\,i,c,t} = \alpha_i + \tau_t + \beta_1\, BSE_{c,t-1} + \beta_2\, BSE_{c,t-1} \cdot crisis + \beta_3\, \mathrm{X}_{i,c,t-1} + \varepsilon_{\,i,c,t}\,, \quad \cdots (13)$$

where i indexes' firms, c indexes countries. α_i and τ_t's are firm and time fixed effects. $Inv_{\,i,t}$ is capital investment by firm i in country c in year t. The variable of interest is the

[14] Variables are defined in Table A1 in the Appendix.

interaction term between the BSE index and the crisis dummy. $X_{i,t}$ is the vector of controls, including firm-level cash flow to assets, log of market capitalization, Tobin's Q, leverage, and country-level real GDP growth. A positive interaction term ($\beta_2 > 0$) would imply that during an economic crisis, firms in economies with efficient banking institutions exhibit a reduced decline in investments compared to those in countries with less efficient banking institutions.

Table 3 presents the findings of estimating equation (13). To account for to account for cross-correlation ($\varepsilon_{i,t}$ and $\varepsilon_{k,t}$) and serial correlation ($\varepsilon_{i,t}$ and $\varepsilon_{i,s}$), we cluster the standard errors at both country and year levels.[15] Models (1) and (2) estimates the model using firm and year fixed effects. Unconditionally, BSE has no impact on capital investments. However, the interaction effect of BSE and the COVID-19 crisis is positive and statistically significant. We repeat the test using country and industry fixed effects along with year fixed effects and continue to find a significant interaction effect. Our findings strongly support hypothesis 1, which states that the sensitivity of capital investment to an economic crisis is lower for firms operating in economies with efficient banking systems than for firms operating in economies with inefficient banking systems.[16]

To address potential omitted variable bias, we employ an interaction effects approach inspired by Rajan and Zingales (1998) and Bertrand *et al.* (2007). We isolate the impact of BSE on firm-level capital investment by examining differential post-crisis changes across sectors based on their pre-crisis reliance on bank financing. This differential analysis helps to control for economic factors correlated with both BSE and firm investment.

We utilize two proxies for sector-level bank dependence: external finance dependence (Rajan & Zingales 1998) and bank debt (Bertrand *et al.* 2007). External finance dependence is calculated as the ratio of capital expenditure minus cash flow to capital expenditure over the decade (2011-2019). Bank debt is defined as the ratio of debt over the sum of the book value of equity, debt, and trade payables.[17] Both measures are categorized into high and low dependence groups based on 3-digit SIC industry median values in US data.

[15] See, for example, Petersen (2009), Cameron *et al.* (2011), Thompson (2011), and Abadie *et al.* (2023) about adjusting standard errors for clustering. For robustness, we examine our results using alternative standard errors: 1) country clustering, 2) firm clustering, and 3) firm and year clustering. Our results are in fact stronger when these alternative clustering is used to adjust the standard errors.

[16] Using a global sample, we confirm that efficient banks supplied more credit during the Covid-19 crisis. Hence, efficient banks were better able to accommodate higher liquidity demands during the economic crisis. Results are reported in the Appendix Table A2.

[17] Although this proxy includes debt owed to parties other than banks, Bertrand *et al.* (2007) show that its strongly correlates with the actual bank debt.

We estimate equation (13) for high and low external finance dependence (Columns 5 and 6) and high and low bank debt (Columns 7 and 8) subsamples. The interaction between BSE and the crisis dummy is significant only for high-dependence sectors, suggesting that BSE primarily affects firms reliant on bank financing. These results mitigate concerns about omitted variable bias.

[Please Insert Table 3 Here]

To visually contrast capital investment disparities between countries with high and low BSE, we categorize countries as such based on the pre-crisis median BSE score. A figure comparing investment levels across these groups is presented. To isolate unexpected capital investment changes, we extract the residual using an AR(1) model including firm and year fixed effects. Subsequently, we calculate average and 99 percent confidence intervals for both country groups.

Figure 2 illustrates pre- and post-COVID-19 shock averages and confidence intervals. While both groups exhibited parallel investment trends pre-shock, post-shock investment declined more steeply in low BSE countries, indicating their heightened vulnerability to economic shocks.

[Please Insert Figure 2 Here]

5.4. Instrumental Variable (IV) Approach

To address potential reverse causality concerns between banking system efficiency and firm investment, we employ a two-stage instrumental variable (IV) approach. Following Levine (1999) and Levine *et al.* (2000), we leverage legal origin as an instrument for BSE. Legal origin, typically determined by historical colonization, is considered an exogenous factor influencing banking development. Legal systems prioritizing full recovery of bank claims are associated with more developed banking institutions (La Porta *et al.* 1998).

In the first stage, we regress the BSE index on dummy variables representing different legal origins (English, French, Scandinavian, and German) using a sample of over 150 countries. Our results align with previous research (La Porta *et al.* 1997), indicating that German legal systems are associated with higher banking efficiency, while French systems exhibit lower efficiency. Importantly, the *F*-statistic of 26.5 in the first stage exceeds the critical value of 10, mitigating concerns of weak instruments (Staiger & Stock 1997).

In the second stage, we use the predicted values of the BSE index, $\widehat{BSE\ index}$, from the first stage to estimate the impact of exogenous component of banking system efficiency on firm investment during the crisis. As shown in Table 4, the positive and statistically significant interaction term coefficients persist, reinforcing the causal relationship between banking system efficiency and firm investment during the crisis.

To enhance the robustness of our IV strategy, we construct two additional instruments by combining legal origin with indices of debt enforcement efficiency (Djankov *et al.* 2008) and procedural formalism (Djankov *et al.* 2003). These indices capture aspects of legal system efficiency that may influence banking sector development. Both alternative IVs exhibit strong first-stage correlations with the BSE index (F-statistics > 10) and support the main findings.

[Please Insert Table 4 Here]

5.5. Broader Measures of Banking System Efficiency

To assess the potential influence of choosing specific bank characteristics on our baseline findings, we introduce alternative specifications. First, we expand the core characteristics (net interest margin (NIM), lending minus deposit spread, non-interest income ratio, overhead cost ratio, and return on assets (ROA)) to include return on equity (ROE), bank concentration, and top five-bank concentration. Similar to the baseline BSE index, we employ Bayesian PCA to extract the BSE^{8} index. ROE represents a bank's profitability, measured as after-tax net income relative to its yearly averaged equity. Bank concentration is calculated as the share of total commercial banking assets held by the three largest commercial banks in a country. Five-bank concentration reflects the share of assets held by the five largest banks. On average, the BSE^{8} index captures approximately 30 percent of the variation in the crude banking efficiency measures.

Second, we incorporate two additional characteristics related to bank stability: bank credit to bank deposits and liquid assets to deposits and short-term funding. Using Bayesian PCA, we extract the alternative BSE^{10} index.

Employing both alternative indices yields positive and significant interaction terms with the crisis dummy. This consistency strengthens the robustness of our findings to bank characteristic selection. For brevity, we report the detailed findings in Appendix Table A3.

5.6. Banking System Efficiency and Investment: Robustness Analysis

To assess the robustness of the relationship between BSE and firm investment during crises, we conducted a series of tests. We investigate whether the findings persist when employing: (1) alternative methodology for BSE index construction, (2) BSE index values from two years prior to the crisis, robustness controlling for (3) stock market capitalization, bond market development, and aggregate investment opportunities.

5.6.1. *Alternative BSE Index Construction*

Given the potential impact of BSE index construction methodology on results, we constructed BSE indices using both conventional PCA and probabilistic PCA (PPCA). The latter employs an EM algorithm (Roweis 1997; Tipping & Bishop 1999). Results remained consistent across both methods, indicating the robustness of our findings (Table 5, Panels A and B). In contrast, the IMF's efficiency index lacks any predictive power.[18]

5.6.2. *Predetermined BSE*

To address potential concerns about crisis anticipation influencing current BSE, we estimate the model using BSE index from 2 years prior to the crisis similar to the approach proposed by Duchin *et al.* (2010) (Panel C). The positive and significant coefficient for the interaction term reaffirms the robustness of the findings.

5.6.3. *Stock Market Capitalization and Macroeconomic Controls*

We control for stock market capitalization – total value of all traded shares in a stock market exchange as a percentage of GDP – to separate the effect of banking credit from the ability to access cheap equity financing. The significant impact of BSE persists even after even after controlling for the effects of the stock market. We also control for macroeconomic variables well-documented to influence firm-level investment behavior: GDP growth, interest rate, and inflation rate. Despite these additional controls, the positive relationship between the BSE index and investment remains consistent (Panel D).

[Please Insert Table 5 Here]

[18] Results using the IMF's financial institutions efficiency are reported in the Appendix Table A4.

5.7. Isolating Banking Efficiency Effects

We perform additional robustness checks to isolate the effects of banking system efficiency from the effects of monetary policy and exchange rate movements, capital regulations, access to corporate bond markets, and social distancing regulations.[19]

5.7.1. *Monetary Policy and Exchange Rate*

To disentangle the effects of banking efficiency from monetary policy and exchange rate fluctuations, we focused on the Eurozone. Given the centralized monetary policy under the European Central Bank (ECB) and the prevailing low-interest rate environment prior to the crisis (Benmelech & Tzur-Ilan 2020), we argue that these factors are largely controlled in this setting. Consistent with our hypothesis, firms in Eurozone countries with efficient banking systems exhibited significantly lower capital investment sensitivity to the COVID crisis.

5.7.2. *Capital Regulations*

We also explore whether bank capital regulations influenced our findings. Applying Barth *et al.* (2013) methodology to the World Bank's 2019 Bank Regulation and Supervision Survey, we categorized markets as high or low stringency based on their overall capital stringency score. The analysis reveals that banking efficiency's impact is evident in both high and low capital stringency environments.

5.7.3. *Corporate Bond Markets*

Using data compiled by Cihak *et al.* (2012), we examine the impact of banking efficiency for countries with and without private bond markets. The analysis reveals that banking efficiency's impact is evident in both sub-samples.

5.7.4. *Social Distancing Regulations*

Certain industries bore the brunt of COVID-19-induced social distancing regulations. Koren and Pető (2020) introduce a proxy – the affected share – to quantify firms' adaptability to social distancing restrictions. This measure captures the extent of reliance on remote work arrangements and considers the implications of physical proximity to others, providing a comprehensive assessment of vulnerability to social distancing measures (Pagano *et al.* 2023).

[19] For brevity, all robustness tables are reported in the Appendix Table A5 and A6.

We classify industries as either resilient or non-resilient based on their affected share relative to the median.

Our results indicate that the relationship between BSE and investment is present in both resilient and non-resilient industries. However, the impact of BSE on investment is more pronounced in non-resilient industries, which experienced the brunt of the shock. This finding further emphasizes the critical role of banks in providing credit during crises and highlight the amplified benefits of efficient banking systems in challenging economic conditions.

6. Prioritizing Loan Allocation: Financing Ability vs. Need During Economic Crises

This section examines whether banks prioritize loan allocation based on firms' financing ability, measured by tangible assets and industry sales cyclicality, or their financing need, captured by cash holdings and cash flow sensitivity.

6.1. Collateral Channel

We categorize firms that have high collateral values as those with the ability secure financing. Collateral mitigates information asymmetry and agency costs (Hart & Moore 1994; Kiyotaki & Moore 1997), facilitating loan approval. Collateral also alleviates lending inefficiencies such as local relationship banks rejecting viable projects due to competition from distant transactional lenders (Inderst & Mueller 2007).

To identify firms with higher collateral assets, we employ two proxies: a firm's tangible assets ratio and the cyclicality of durable goods industry sales. Firms with lower tangible assets face restricted credit access when bank risk reassess risk (Berger *et al.* 1996). Additionally, intangible assets are more difficult to quantify, hindering access to external financing (Kroszner *et al.* 2007). For durable goods producers that are highly sensitive to business cycles, a negative demand shock is likely to affect all potential alternative users of a durable producer's assets, consequently reducing tangibility (Almeida & Campello 2007).

As a first proxy for collateral, we use a firm's tangibility ratio of fixed to total investments. Fixed assets, such as property, plant, and equipment, are more readily pledged as collateral compared to intangible capital (Berger *et al.* 1996; Kroszner *et al.* 2007). To differentiate firms based on tangibility levels, we construct an annual ranking based on the firm's tangibility ratio and divide the sample along the median. The indicator variable *High Tangibility* equals one if the firm's tangibility ratio exceeds the annual median within the country, and zero otherwise.

For robustness, we employ industry level *Durability*, which stems from the observation that collateralized borrowing declines when assets in receivership are unlikely to be reallocated to their first-best alternative users, often firms within the same industry (Shleifer & Vishny 1992). Durable goods producers exhibit high sensitivity to business cycles compared to nondurable and services producers. A negative demand shock likely impacts all potential alternative users of a durable producer's assets, thus reducing tangibility (Almeida & Campello 2007). Employing industry input-output accounts, per Gomes *et al.* (2009), we classify consumption good producers into durable and non-durable categories.

We estimate the following model:

$$
\begin{aligned}
Inv_{i,c,t} = {} & \alpha_i + \tau_t \\
& + \beta_1\, BSE_{c,t-1} + \beta_2\, BSE_{c,t-1} \cdot crisis + \beta_3\, BSE_{c,t-1} \cdot crisis \cdot collateral \\
& + \beta_5\, crisis \cdot collateral + \beta_6\, \mathrm{X}_{i,t-1} + \varepsilon_{i,t}\,, \qquad \cdots (14)
\end{aligned}
$$

where the coefficient on the double interaction term β_3 is our variable of interest. According to the collateral hypothesis, we expect β_3 will be positive.

Table 6 presents the regression results for equation (14), revealing a positive and statistically significant coefficient for the double interaction term. This indicates that collateral-rich firms can effectively utilize bank credit as a hedge against cash flow fluctuations. Consequently, access to efficient banking institutions mitigates the negative impact of economic crises on firm investment.

We further examine equation (14) for subsamples of firms in industries with high and low external financing dependence. The collateral effect is evident only in the sample of firms reliant on external financing, strengthening the validity of the BSE index as a measure of banking efficiency. These results support Hypothesis 2, suggesting that the influence of banking efficiency on investment is more pronounced during economic downturns, especially for firms with high collateral assets.

[Please Insert Table 6 Here]

6.2. Financially Constrained Firms

We next examine whether the safety net provided by banking systems efficiency extends to genuinely credit-constrained firms, rather than those with the capacity to secure financing. Specifically, we investigate if the positive impact of BSE on investment during economic crises is amplified for firms experiencing financial constraints.

The marginal value of cash is significantly higher for firms with valuable investment opportunities but face greater financing constraints. Hence, constrained firms are more likely to hold cash to safeguard against future cash flow risks (e.g., Kim *et al.* 1998; Opler *et al.* 1999; Faulkender & Wang 2006). In addition, firms that face capital market frictions are likely to save cash out of cash flow (Almeida *et al.* 2004). Sufi (2009) show that firms without access to a line of credit are more likely to save cash out of cash flow. Hence, two metrics are employed to assess firm-level constraints: (1) firm cash holdings and (2) sensitivity of cash flow to changes in cash holdings.

Firm cash holdings are cash scaled by total assets. To quantify the cash-cash flow sensitivity, we regress cash holdings on cash flow while incorporating lagged control variables for market value, leverage, and Tobin's *Q*, utilizing data from the past decade. We construct a dummy variable (*High Cash-CF Sensitivity*) to identify firms with financial constraints. This variable takes a value of 1 if the cash-to-cash flow sensitivity falls within the top tercile (by country-year) and 0 otherwise.

Our findings, presented in Table 7, do not provide support for the hypothesis that efficient banking systems allocate a larger share of their lending to financially constrained firms during periods of economic downturn. This suggests that the effect of BSE on firm investment may not extend to firms that are genuinely in need of financing.

[Please Insert Table 7 Here]

7. Implications on Non-Financial Firm Restructuring Activities

Having established that BSE prioritizes lending based on financing ability over need, we now examine the consequences of these stringent lending practices. We investigate the impact of efficient banks for a number of performance metrics: investment, employment, profitability, and firm value. We also examine whether the effects are stronger for pre-crisis high performing firms. Following Bertrand *et al.* (2007), we employ mean pre-crisis ROA as a proxy for firm performance. To capture performance heterogeneity, we introduce a double interaction term involving the BSE index, a crisis dummy, and mean ROA.

Table 8 presents the results. The crisis induced reduction in both investment and employment is significantly reduced for those firms in countries with high banking system efficiency. However, we find no difference in the effect between high performing and underperforming firms.

The effects are much more dependent on firm performance for leverage, profitability, and firm value. Positive coefficients on the double interaction term indicates that, during economic crises, leverage, profitability, and firm value decrease for firms that were (pre-crisis) underperforming in countries with efficient banking systems. This suggests a credit allocation bias towards high-performing firms in countries with efficiently function banking systems. Our results strongly support the hypothesis that efficient banking systems can induce critical restructuring within non-financial firms, thereby enhancing overall market efficiency.

[Please Insert Table 8 Here]

8. Conclusion

Efficient banking systems are characterized by high competition, low interest margins, and low overhead costs. Based on this definition, we construct novel, time-varying indexes of efficiency in the banking system based on a comprehensive set of characteristics. To address data limitations, we employed a Bayesian principal component analysis, enabling us to capture unobserved dimensions of banking system efficiency. Our findings offer fresh insights into the role of efficient banking systems in mitigating the adverse impact of economic crises on capital investment. Specifically, we demonstrate that firms with access to efficient banking institutions exhibit lower sensitivity of capital investment to economic shocks, particularly those operating in sectors reliant on external financing.

Moreover, our analysis reveals that efficient banks prioritize lending to firms with higher levels of collateralizable assets during crises, suggesting a superior ability to assess and manage credit risk. However, we find no evidence that efficient banks preferentially lend to financially constrained firms, indicating that the safety net function of efficient banking systems may be limited in scope.

Our results further highlight the disciplinary role of efficient banking systems. By imposing stricter lending standards during crises, these institutions contribute to improved efficiency in the non-financial sector, as evidenced by reduced profitability, and firm value for pre-crisis underperforming firms.

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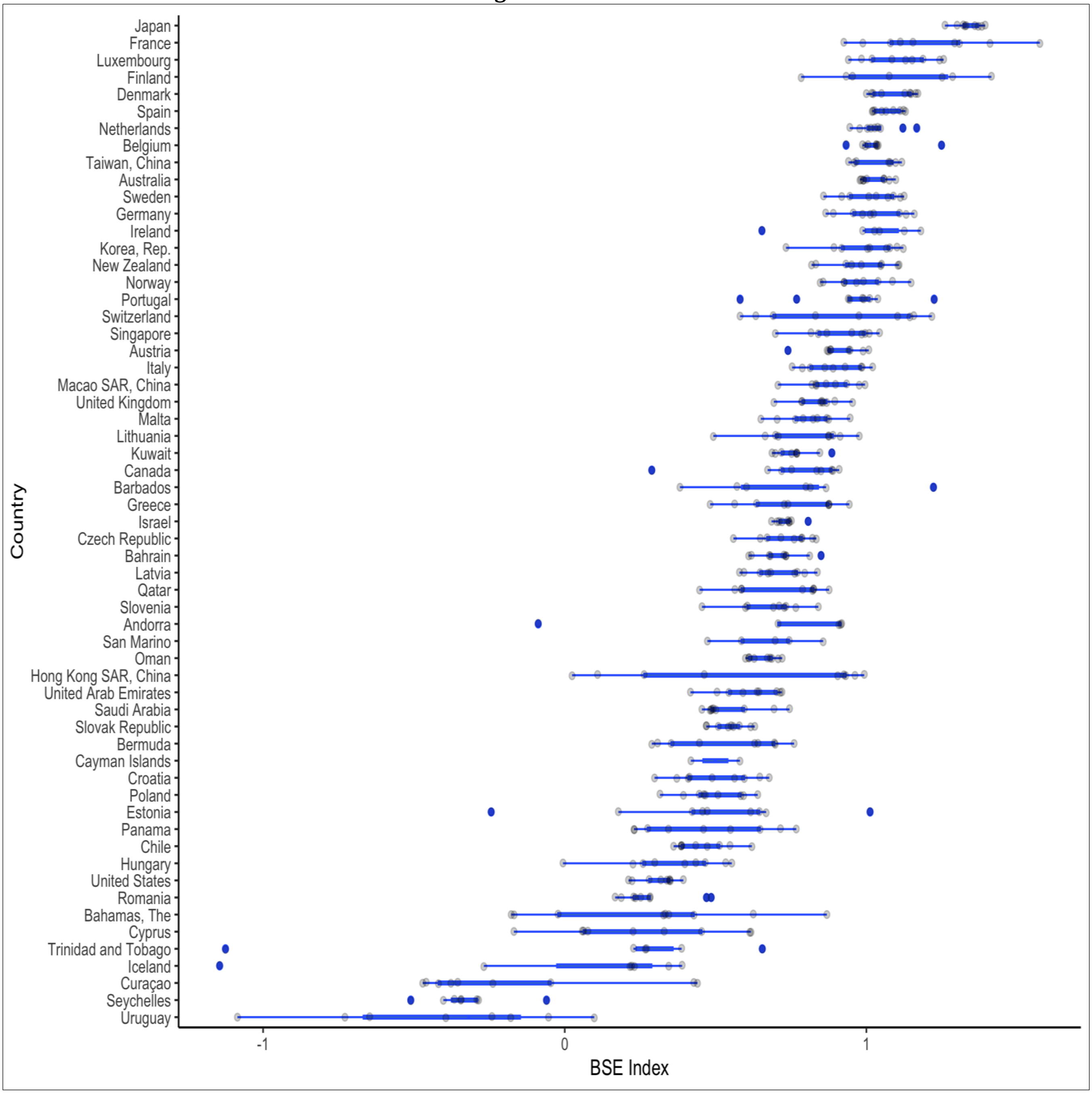
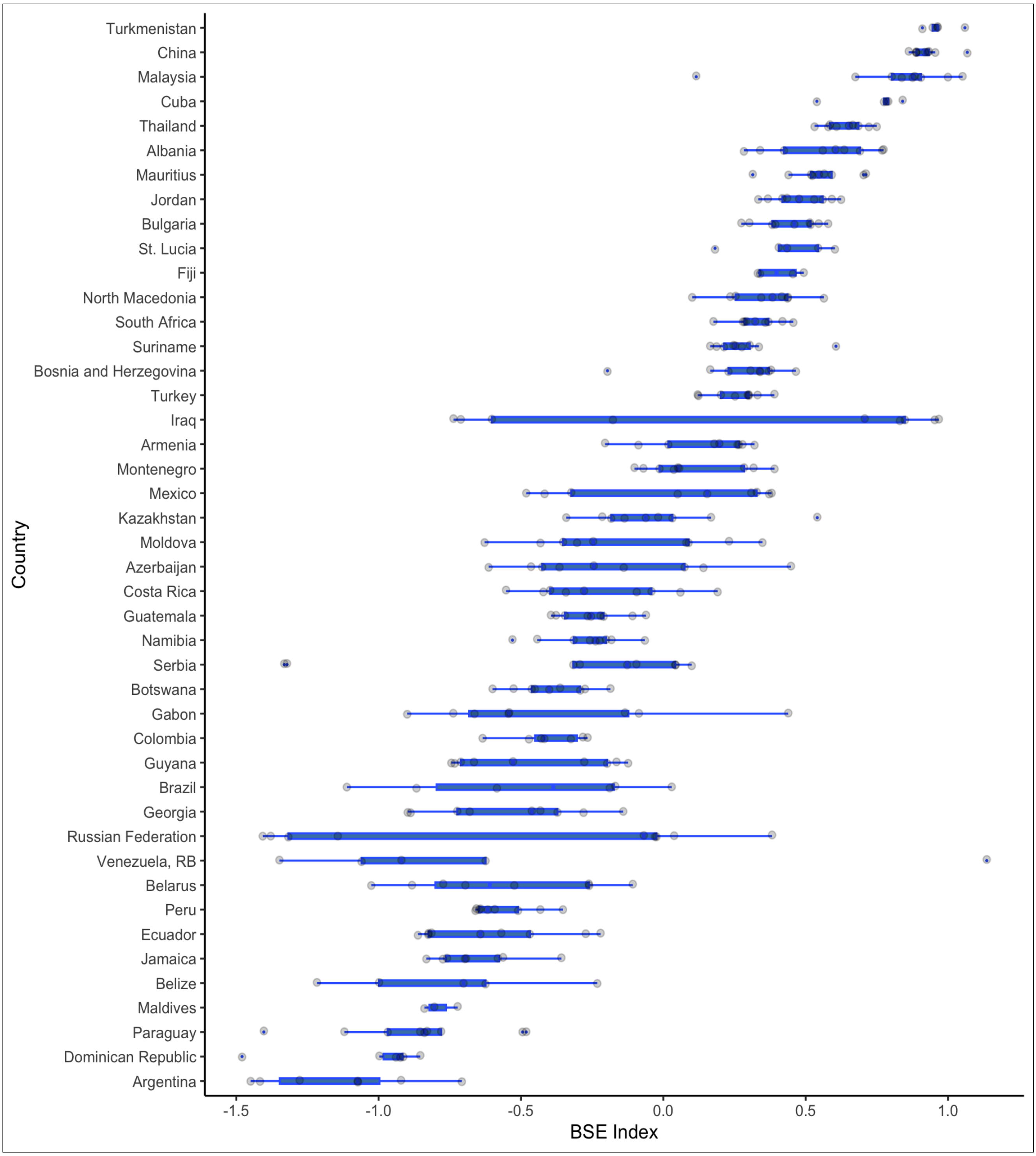
Figure 1. Banking System Efficiency (BSE) by Economy

Note: This figure illustrates the BSE index for each country-year. The BSE index is derived as the first principal component extracted through the Bayesian PCA methodology detailed in Section 2. For each country, the blue line represents the interquartile range (IQR), which encapsulates the central 50% of the BSE index distribution. Panel A, B, and C depicts high-income economies, middle-income economies, and low-income economies, respectively.

Panel A. High Income Economies



Panel B. Middle-Income Markets



Panel C. Lower-Income Markets

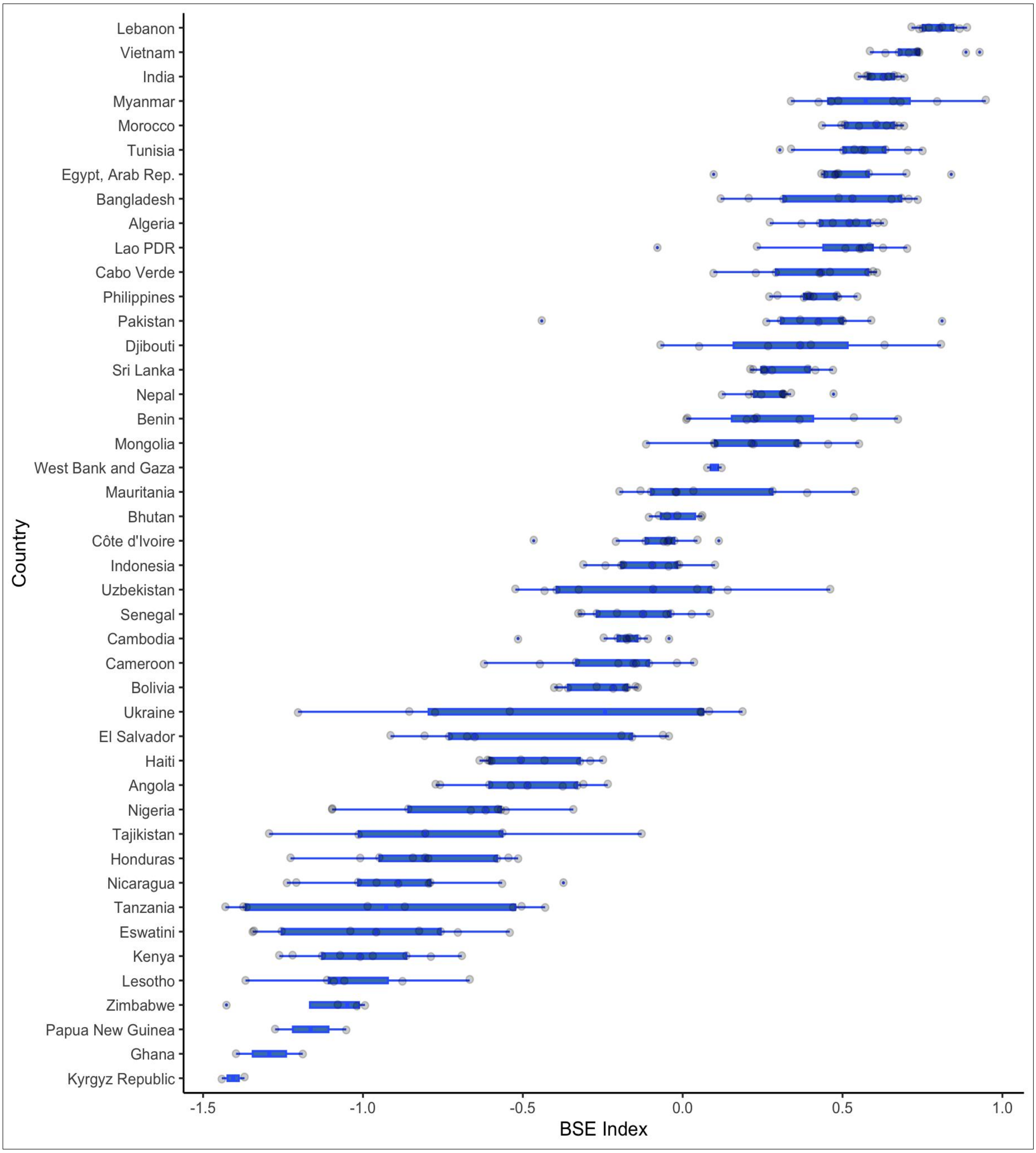


Figure 2. Capital Investment Dynamics During COVID-19 Crisis

Note: This figure illustrates the average firm capital investment for countries with varying levels of banking efficiency. Countries with an BSE index below the pre-crisis median are classified as *Low BSE*, while those with an BSE index above the median are classified as *High BSE*. This figure plots the estimated residuals (unexplained variation) using a regression of capital investments on lagged capital investment with firm and year fixed effects. The residuals for High BSE and Low BSE economies are plotted in blue and red, respectively. The figure depicts the average and the 99 percent confidence intervals.

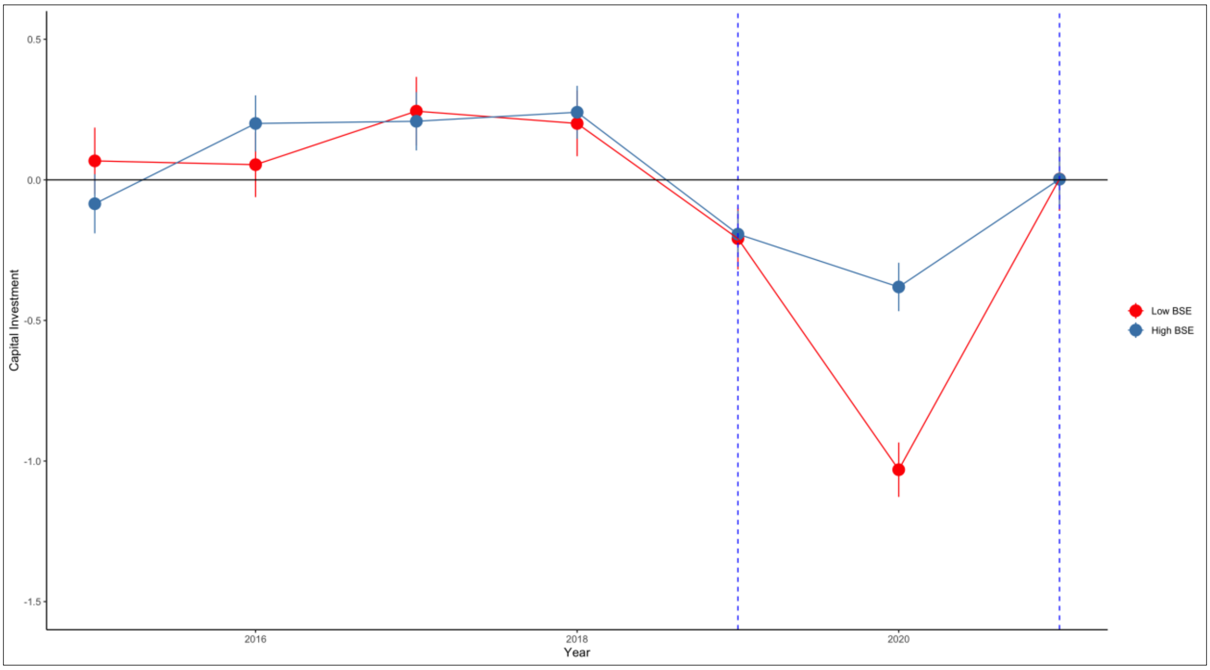


Table 1. Validating the BSE Index

Note: This table presents the estimates from the simulation model and the out-of-sample tests. Panel A presents the results from the simulation which intends to analyze the accuracy of the banking system efficiency (BSE) index based on the Bayesian PCA. The dataset consists of the crude efficiency characteristics net interest margin, lending minus deposits spread, noninterest income to total income, overhead costs to total assets, and return on assets. For the simulation, we use the sample of country-years with non-missing observations. In the first step, we estimate the 1st principal component using the standard PCA. In the second step, we randomly drop a certain percentage of observations and estimate the BSE index based on the Bayesian PCA. We report the mean and the 95 percent confidence level for correlation between the BSE index and the 1st principal component using a standard PCA. Panel B presents the R^2 estimates for the out-of-sample tests. We use banking efficiency indexes (BSE index and IMF's FIE index) constructed solely with data up to 2017. We then estimate the correlation between the 2017 index and NIM, lending minus deposit spread, bank overhead costs, and bank ROA for 2018, 2019, and 2020. We report the R^2 estimates from each regression.

Panel A. Simulation Results

Percentage of Missing Values	Correlation Coefficient	Confidence Interval
5%	0.993	(0.933, 0.994)
6%	0.991	(0.991, 0.992)
7%	0.989	(0.988, 0.990)
8%	0.988	(0.987, 0.989)
9%	0.985	(0.984, 0.986)
10%	0.983	(0.981, 0.984)
11%	0.981	(0.979, 0.982)
12%	0.978	(0.977, 0.980)
13%	0.976	(0.974, 0.978)
14%	0.975	(0.973, 0.976)
15%	0.972	(0.970, 0.974)

Panel B. Out-of-sample Predictive Power (R^2 Estimates)

Year	Net Interest Margin		Lending-Deposit Spread		Bank Overhead Costs		Bank Profitability	
	BSE Index	IMF's Index	BSE Index	IMF'' Index	BSE Index	IMF's Index	BSE Index	IMF's Index
2018	0.879	0.487	0.409	0.256	0.735	0.508	0.401	0.142
2019	0.878	0.475	0.403	0.307	0.761	0.483	0.454	0.200
2020	0.789	0.458	0.317	0.231	0.639	0.421	0.268	0.098

Table 2. Summary Statistics

Note: This table reports the mean statistics of key variables for a sample of Compustat Global yearly observations between 2011 and 2021. The sample encompasses publicly listed firms from 55 countries. Excluded from the analysis are financial institutions, firm-year observations with a non-positive book value of total assets or book value of common equity, and observations lacking the accounting information necessary for the construction of key variables. N represents the total number of firm-year observations. The BSE Index serves as a measure of efficiency in the banking system. Capital Investment represents the ratio of annual capital expenditure to the book value of total assets at the beginning of the fiscal year. All accounting figures are denominated in U.S. dollars, and all financial variables are winsorized at the 1st and 99th percentiles by country.

	2011-2019			2020-2021		
Country	N	BSE Index	Capital Investment	N	BSE Index	Capital Investment
Argentina	337	-1.134	0.056	76	-2.319	0.039
Australia	7170	1.029	0.081	1394	1.003	0.074
Austria	381	0.896	0.054	68	1.071	0.053
Bangladesh	1142	0.463	0.062	366	0.868	0.046
Belgium	577	1.056	0.045	115	1.074	0.037
Brazil	1314	-0.752	0.036	269	-1.002	0.030
Bulgaria	357	0.421	0.042	95	0.551	0.025
Canada	807	0.699	0.070	192	0.876	0.062
Chile	482	0.478	0.043	148	0.450	0.037
China	25002	0.930	0.059	7740	0.851	0.054
Croatia	474	0.516	0.050	99	0.484	0.046
Cyprus	401	0.335	0.033	77	0.162	0.037
Denmark	652	1.096	0.040	137	1.182	0.037
Egypt	775	0.535	0.038	215	0.184	0.037
Finland	573	1.052	0.041	224	1.281	0.039
France	3590	1.151	0.039	711	1.538	0.039
Germany	3323	1.010	0.042	651	1.158	0.036
Greece	1211	0.796	0.028	204	0.719	0.034
Hong Kong	7534	0.586	0.035	2001	0.980	0.026
India	20169	0.622	0.051	5146	0.524	0.040
Indonesia	2278	-0.116	0.060	683	-0.072	0.035
Israel	1615	0.731	0.036	375	0.782	0.033

Italy	1514	0.882	0.034	401	1.100	0.034
Japan	23026	1.352	0.034	5370	1.350	0.030
Jordan	786	0.518	0.036	142	0.481	0.026
Kenya	159	-1.108	0.057	30	-0.384	0.030
Korea	8569	1.011	0.045	2981	0.863	0.041
Kuwait	717	0.749	0.038	132	0.867	0.025
Malaysia	6670	0.786	0.038	1555	0.921	0.031
Mauritius	95	0.594	0.026	69	0.672	0.019
Mexico	438	0.089	0.062	110	-0.383	0.034
Netherlands	434	1.028	0.035	83	1.173	0.025
New Zealand	719	1.017	0.049	171	0.829	0.035
Nigeria	625	-0.717	0.065	140	-0.430	0.050
Norway	972	0.988	0.057	209	0.847	0.049
Oman	540	0.645	0.053	119	0.709	0.029
Pakistan	2318	0.377	0.060	581	0.355	0.047
Peru	540	-0.572	0.052	129	-0.305	0.029
Philippines	1108	0.416	0.054	269	0.217	0.030
Poland	3563	0.497	0.050	886	0.549	0.048
Romania	842	0.289	0.028	230	0.254	0.024
Russian Federation	979	-1.147	0.069	201	0.069	0.056
Saudi Arabia	882	0.562	0.060	253	0.521	0.033
Singapore	3902	0.885	0.044	821	1.000	0.025
South Africa	1383	0.347	0.052	243	0.456	0.035
Spain	767	1.062	0.038	180	1.220	0.042
Sri Lanka	1107	0.336	0.048	366	0.313	0.034
Sweden	3158	1.023	0.026	984	1.105	0.024
Switzerland	1098	0.851	0.041	231	1.218	0.040
Thailand	4054	0.654	0.058	1115	0.608	0.036
Turkey	1611	0.236	0.050	453	0.226	0.048
United Arab Emirates	356	0.599	0.043	78	0.781	0.026
U.K.	5992	0.830	0.041	1174	0.813	0.029
U.S.	23465	0.337	0.051	4657	0.320	0.036
Vietnam	2588	0.758	0.055	607	0.551	0.037

Table 3. Banking System Efficiency and Firm Investment

Note: This table presents regression estimates of firm investment on country-level BSE indices, utilizing a sample of Compustat Global firms from 2011to 2021. The sample comprises publicly traded firms from 55 markets. We exclude financial firms, firm-year observations with non-positive book values of total assets or common equity, or those lacking accounting information required for key variable construction. The BSE Index is constructed using a Bayesian principal component analysis (B-PCA) approach, incorporating net interest margin, lending minus deposits spread, non-interest income to total income, overhead costs to total assets, and the bank's return on assets. Capital Investment denotes the ratio of annual capital expenditure to the book value of total assets at the beginning of the fiscal year. CF/TA represents the ratio of annual cash flows to the book value of total assets at the beginning of the fiscal year. Ln Mkt Cap denotes the market capitalization in natural logarithm at the end of the fiscal year. Tobin's *q* signifies the ratio of the book value of assets plus the market value of common equity minus the book value of common equity and deferred taxes to the book value of assets, measured at the end of the fiscal year. Leverage represents the ratio of the book value of debt to the book value of total assets at the beginning of the fiscal year. GDP Growth represents the annual growth of GDP per capita. Crisis is an indicator variable with a value of 1 for the years 2020 and 2021, and zero otherwise. Following Rajan and Zingales (1998), external finance dependence is measured by summing firm capital expenditure minus cash flows over the decade (2010-2019) and scaling it by the sum of capital expenditure. The median value at the three-digit SIC level is then calculated based on US data. High External Fin Dependent equals one if the industry's external finance dependence is above the median, and zero otherwise. Following Bertrand *et al.* (2007), we define bank debt as the ratio of debt over the sum of the book value of equity, debt, and trade payables. This metric is then used to categorize sectors into high and low bank debt industries based on the median value for three-digit SIC industries in the US data. All accounting figures are denominated in U.S. dollars, and all financial variables are winsorized at 1 and 99 percentiles by country. All regressions incorporate firm and year-fixed effects. *T*-statistics in parentheses are based on standard errors adjusted for country and year clustering. Observations represent the total number of firm-year observations. Significance levels are indicated by *** for 1%, ** for 5%, and * for 10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var = Capital Investment	Full Sample				High External Finance Dependent	Low External Finance Dependent	High Bank Debt Sectors	Low Bank Debt Sectors
BSE Index $_{t-1}$	0.002	0.002	0.001	-0.000	0.002	0.001	0.002	0.001
	(1.008)	(0.694)	(0.308)	(-0.193)	(0.910)	(0.248)	(0.868)	(0.503)
BSE Index $_{t-1}$ × *Crisis*		0.006***		0.007***	0.006***	0.004	0.008***	0.004*
		(3.686)		(3.300)	(4.138)	(1.389)	(4.806)	(2.082)
GDP Growth $_{t-1}$	0.060	0.056	0.059	0.055	0.054	0.062	0.047	0.073
	(1.597)	(1.369)	(1.796)	(1.474)	(1.331)	(1.244)	(1.265)	(1.530)
CF/TA $_{t}$	0.058***	0.058***	0.067***	0.067***	0.054***	0.067***	0.074**	0.048***
	(4.097)	(4.080)	(4.239)	(4.222)	(3.569)	(4.968)	(2.968)	(4.327)

Ln Mkt Cap $_{t-1}$	0.002**	0.002**	0.001***	0.001***	0.003**	0.001	0.004***	0.001
	(2.327)	(2.272)	(3.540)	(3.566)	(2.231)	(0.713)	(3.177)	(0.756)
Tobin's Q $_{t-1}$	0.004***	0.004***	0.003***	0.003***	0.005***	0.003***	0.005**	0.004***
	(4.706)	(4.714)	(4.162)	(4.148)	(4.464)	(4.149)	(2.704)	(6.828)
Leverage $_{t-1}$	-0.059***	-0.059***	0.010**	0.010**	-0.064***	-0.052***	-0.072***	-0.049***
	(-9.950)	(-9.562)	(2.392)	(2.438)	(-10.548)	(-7.553)	(-10.494)	(-6.691)
Firm FE	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	No	No	No	No
Industry FE	No	No	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	231,097	231,097	230,480	230,480	152,522	72,844	91,578	131,964
Adjusted R^2	0.436	0.436	0.145	0.145	0.442	0.402	0.435	0.423

Table 4. Instrumental Variable (IV) Approach

Note: This table presents the 2nd stage estimates of Equation (5) for the period from 2011 to 2021. The sample comprises publicly traded firms from 55 markets. In the first stage, we regress the BSE index on the instrumental variable. In the second stage, we instrument the BSE index using the predicted values from the first stage, $\widehat{BSE\ Index}_t$. In Specification 1, we use legal origin (indicators for UK common law, German civil law, French civil law, and Scandinavian civil law) to instrument the BSE index. In Specification 2, we use legal origin plus the debt enforcement index – a country-level measure the efficiency of debt enforcement – by Djankov *et al.* (2008) as instruments. In Specification 3, we use legal origin plus the procedural formalism index – measure of the effectiveness of courts as mechanisms of resolving simple disputes – by Djankov *et al.* (2003) as instruments. All models contain the same set of controls in the baseline model in Table 3. Crisis is an indicator variable with a value of 1 for the years 2020 and 2021, and zero otherwise. All accounting figures are denominated in US dollars, and all financial variables are winsorized at 1 and 99 percentiles by country. All regressions incorporate firm and year-fixed effects. *T*-statistics in parentheses are based on standard errors adjusted for country and year clustering. Observations represent the total number of firm-year observations. Significance levels are indicated by *** for 1%, ** for 5%, and * for 10%.

2011-2021 Dependent Var = Capital Investment	(1) Legal Origin	(2) Legal Origin and Debt Enforcement	(3) Legal Origin and Formalism
$\widehat{BSE\ Index}^1_{t-1}$ × Crisis	0.008***		
	(4.034)		
$\widehat{BSE\ Index}^2_{t-1}$ × Crisis		0.006**	
		(3.185)	
$\widehat{BSE\ Index}^3_{t-1}$ × Crisis			0.010***
			(6.630)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	206,450	175,577	204,721
Adjusted R^2	0.442	0.471	0.443
First-stage *F*-Statistic	26.5	21.6	17.2

Table 5. Banking System Efficiency and Investment: Robustness Analysis

Note: This table presents regression estimates of firm investment on country-level BSE indexes, employing a sample of Compustat Global firms from 2011 to 2021. The sample comprises publicly listed firms from 55 markets. Financial firms, firm-year observations with non-positive book values of total assets or book value of common equity, and those lacking the accounting information necessary for variable construction are excluded from the analysis.

- *Panel A:* The conventional BSE index is computed using a standard principal component analysis (excluding missing data) based on net interest margin, lending minus deposits spread, noninterest income to total income, overhead costs to total assets, and bank's return on assets.
- *Panel B:* BSE is proxied using a probabilistic principal component analysis (P-PCA). P-PCA combines an expectation-maximization (EM) approach for PCA with a probabilistic model.
- *Panel C:* The regression estimates of yearly investment on country-level BSE index measured in year *t-2* are presented.
- *Panel D* controls for the effects of stock market capitalization to GDP and macroeconomic drivers of investment, including GDP growth rate, inflation rate, and interest rate.

All regressions include the baseline controls and restrictions. The crisis indicator variable takes a value of 1 for the years 2020 and 2021, and zero otherwise. *T*-statistics in parentheses are based on standard errors adjusted for country and year clustering. Significance levels are indicated by asterisks: *** for 1%, ** for 5%, and * for 10%.

Panel A. Index Estimated using Conventional PCA

Dependent Var = Capital Investment	(1)	(2)
PCA_{t-1}	0.002	0.002
	(1.339)	(1.235)
$PCA_{t-1} \times$ Crisis		0.003*
		(1.881)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	120,172	120,172
Adjusted R^2	0.422	0.422

Panel B. Index Estimated using Probabilistic PCA (P-PCA)

Dependent Var = Capital Investment	(1)	(2)
$P\text{-}PCA_{t-1}$	-0.000	-0.001
	(-0.166)	(-0.560)
$P\text{-}PCA_{t-1} \times$ Crisis		0.004***
		(3.830)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	231,097	231,097
Adjusted R^2	0.435	0.436

Panel C. BSE Index 2-years Prior to Crisis

Dependent Var = Capital Investment	(1)	(2)	(3)	(4)	(5) High External Finance Dependent	(6) Low External Finance Dependent	(7) High Bank Debt Sectors	(8) Low Bank Debt Sectors
	Full Sample							
BSE Index $_{t-2}$	0.002	0.001	0.001	-0.000	0.001	0.002	0.002	0.001
	(0.865)	(0.585)	(0.396)	(-0.142)	(0.501)	(0.814)	(0.682)	(0.537)
BSE Index $_{t-2}$ × Crisis		0.006**		0.008***	0.007**	0.004	0.009***	0.003
		(2.790)		(3.307)	(2.986)	(1.343)	(3.296)	(1.673)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	No	No	No	No
Country FE	No	No	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	213,511	213,511	212,933	212,933	140,900	67,288	84,405	122,152
Adjusted R^2	0.438	0.438	0.138	0.138	0.445	0.410	0.437	0.428

Panel D. Controlling for Stock Market Capitalization and Other Macroeconomic Factors

Dependent Var = Capital Investment	(1)	(2)
BSE Index $_{t-1}$	0.001	0.003
	(0.471)	(0.917)
BSE Index $_{t-1}$ × Crisis	0.006**	0.006***
	(3.161)	(3.288)
GDP Growth $_{t-1}$	0.056	0.097
	(1.303)	(1.451)
Stock Market Capitalization to GDP $_{t-1}$	0.002	
	(1.195)	
Inflation Rate $_{t-1}$		0.001
		(1.810)
Interest Rate $_{t-1}$		-0.000
		(-1.594)
Unemployment $_{t-1}$		-0.002*
		(-1.889)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	215,175	172,978
Adjusted R^2	0.437	0.440

Table 6. Banking System Efficiency, Collateral Assets, and Firm Investment

Note: This table presents regression estimates of firm investment on BSE indexes based on a sample of Compustat Global firms from 2011 to 2021. The sample encompasses publicly listed firms from 55 economies. We excluded financial firms, firm-year observations with a non-positive book value of total assets or book value of common equity, or without accounting information necessary for key variable construction. Capital Investment represents the ratio of annual capital expenditure to the book value of total assets at the beginning of the fiscal year. Crisis is an indicator variable designated with a value of 1 for the years 2020 and 2021, and zero otherwise. High Tangibility is an indicator variable that equals 1 if the firm's tangibility ratio (fixed assets to book value of total assets) exceeds the annual median within the country, and zero otherwise. Durability is an indicator variable that equals 1 if the firm operates in a nondurable industry, and zero if the firm operates in a durable industry. All regressions incorporate firm and year-fixed effects. *T*-statistics enclosed in parentheses are based on standard errors adjusted for country and year clustering. Observations represent the total number of firm-year observations. Significance levels are indicated by asterisks: *** for 1%, ** for 5%, and * for 10%.

Panel A. Tangible Assets

Dependent Var = Capital Investment	(1)	(2)	(3) High External Finance Dependent	(4) Low External Finance Dependent	(5) High Bank Debt Sectors	(6) Low Bank Debt Sectors
	Full Sample					
BSE Index $_{t-1}$	0.003	0.003	0.003	0.002	0.004	0.002
	(1.169)	(1.177)	(1.566)	(0.459)	(1.552)	(0.871)
BSE Index $_{t-1}$ × High Tangibility $_{t-1}$	-0.000	-0.002	-0.002	-0.001	-0.003	-0.002
	(-0.203)	(-0.942)	(-1.188)	(-0.509)	(-1.309)	(-0.830)
BSE Index $_{t-1}$ × *Crisis*		0.003**	0.002**	0.004*	0.004***	0.002
		(2.376)	(2.305)	(1.938)	(4.758)	(1.383)
BSE Index $_{t-1}$ × High Tangibility $_{t-1}$ × *Crisis*		0.007***	0.008***	0.001	0.008**	0.005*
		(3.310)	(3.239)	(0.390)	(2.731)	(2.146)
High Tangibility $_{t-1}$ × *Crisis*		-0.016***	-0.017***	-0.012**	-0.016***	-0.015***
		(-4.158)	(-3.574)	(-2.930)	(-3.476)	(-4.241)
High Tangibility $_{t-1}$	0.002	0.005	0.005	0.003	0.005	0.006*
	(0.698)	(1.584)	(1.445)	(1.184)	(1.473)	(1.852)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	152,522	72,844	152,522	72,844	91,578	131,964
Adjusted R^2	0.443	0.403	0.443	0.403	0.436	0.424

Panel B. Durability

Dependent Var = Capital Investment	(1)	(2)	(3) High External Finance Dependent	(4) Low External Finance Dependent	(5) High Bank Debt Sectors	(6) Low Bank Debt Sectors
	Full Sample					
BSE Index $_{t-1}$	0.006	0.007	0.005	0.009*	0.009	0.005
	(1.738)	(1.812)	(1.286)	(2.136)	(1.707)	(1.400)
BSE Index $_{t-1}$ × Durability $_{t-1}$	-0.003	-0.004	-0.003	-0.006	-0.006	-0.004
	(-0.705)	(-0.829)	(-0.352)	(-1.306)	(-1.126)	(-0.781)
BSE Index $_{t-1}$ × *Crisis*		-0.003	-0.005	-0.002	-0.004	-0.001
		(-0.633)	(-0.860)	(-0.634)	(-0.640)	(-0.341)
BSE Index $_{t-1}$ × Durability $_{t-1}$ × *Crisis*		0.007**	0.009**	0.004	0.012**	0.001
		(2.795)	(2.661)	(1.186)	(2.989)	(0.834)
Durability $_{t-1}$ × *Crisis*		-0.003	-0.003	-0.006*	-0.008	0.003
		(-0.796)	(-0.552)	(-1.857)	(-1.664)	(1.146)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	152,522	72,844	152,522	72,844	91,578	131,964
Adjusted R^2	0.443	0.403	0.443	0.403	0.436	0.424

Table 7. Banking System Efficiency, Financial Constraints, and Firm Investment

Note: This table presents regression estimates of firm investment on country-level BSE indexes using a sample of Compustat Global firms from 2011 to 2021. The sample encompasses publicly listed companies from 55 economies. Financial firms, firm-year observations with non-positive book values of total assets or common equity, or instances lacking accounting information necessary for key variable construction, were excluded. Capital Investment is the ratio of annual capital expenditure to the book value of total assets at the fiscal year's commencement. Crisis is an indicator variable assigned a value of 1 for the years 2020 and 2021, and zero otherwise. High Cash is a dummy variable that takes a value of 1 if firm cash holding falls above country annual median and 0 otherwise. High Cash-CF Sensitivity is a dummy variable that takes a value of 1 if the cash-to-cash flow sensitivity falls above median (by country-year) and 0 otherwise. All accounting figures are in US dollars, and all financial variables are winsorized at 1st and 99th percentiles by country. Firm and year-fixed effects are included in all regressions. *T*-statistics in parentheses are based on standard errors adjusted for country and year clustering. Observations represent the total number of firm-year observations. Significance levels are indicated by asterisks: *** for 1%, ** for 5%, and * for 10%.

Dependent Var = Capital Investment	(1)	(2)	(3)	(4)
BSE Index $_{t-1}$	0.002	0.001	0.003	0.001
	(0.630)	(0.251)	(1.426)	(0.763)
BSE Index $_{t-1}$ × *Crisis*		0.007**		0.006***
		(2.993)		(3.912)
BSE Index $_{t-1}$ × High Cash $_{t-1}$	0.001	0.002		
	(0.594)	(0.716)		
High Cash $_{t-1}$	0.008***	0.007***		
	(5.185)	(4.302)		
BSE Index $_{t-1}$ × High Cash $_{t-1}$× *Crisis*		-0.001		
		(-0.509)		
High Cash $_{t-1}$× *Crisis*		0.002		
		(0.849)		
BSE Index $_{t-1}$ × High Cash-CF Sensitivity $_{t-1}$			0.000	0.001
			(0.582)	(0.912)
High Cash-CF Sensitivity $_{t-1}$			-0.000	-0.000
			(-0.138)	(-0.550)
BSE Index $_{t-1}$ × High Cash-CF Sensitivity $_{t-1}$ × *Crisis*				-0.001
				(-1.250)
High Cash-CF Sensitivity $_{t-1}$ × *Crisis*				0.002*
				(1.818)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	231,097	231,097	164,771	164,771
Adjusted R-squared	0.438	0.438	0.457	0.458

Table 8. Banking System Efficiency and Firm Restructuring Activities

Note: This table presents regression estimates of firm investment on country-level BSE indexes using a sample of Compustat Global firms from 2011 to 2021. Financial firms, firm-year observations with non-positive book value of total assets or book value of common equity, and those lacking accounting information necessary for key variable construction are excluded. Crisis is an indicator variable with a value of 1 for the years 2020 and 2021, and zero otherwise. Mean ROA is the firm's average ROA between 2010 to 2019. Baseline controls and restrictions are included in all regressions. All accounting figures are in US dollars, and all financial variables are winsorized at 1 and 99 percentiles by country. Firm and year-fixed effects are included in all regressions. *T*-statistics in parentheses are based on standard errors adjusted for country and year clustering. Observations represent the total number of firm-year observations. Significance levels are indicated by asterisks: *** for 1%, ** for 5%, and * for 10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var =	Capital Investment		Employment		Profitability		Firm Value	
BSE Index t-1	0.001	0.002	-0.142*	-0.220**	0.001	0.000	0.240	0.164
	(0.415)	(0.640)	(-2.044)	(-2.305)	(0.631)	(0.100)	(0.565)	(0.525)
BSE Index t-1 × *Crisis*	0.007**	0.005*	0.085***	0.072*	0.002	-0.005*	-0.028	-0.368*
	(3.049)	(2.040)	(5.128)	(2.141)	(0.717)	(-2.030)	(-0.223)	(-2.222)
BSE Index t-1 × Mean ROA × *Crisis*		0.008		0.174		0.056**		1.689*
		(0.528)		(0.668)		(2.327)		(1.957)
BSE Index t-1 × Mean ROA		-0.021		0.927		0.002		-0.853
		(-1.048)		(1.674)		(0.070)		(-0.530)
Mean ROA × *Crisis*		-0.038**		0.212		-0.138***		-2.036*
		(-2.537)		(0.716)		(-6.488)		(-1.995)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	231,097	201,613	153,303	136,057	231,097	201,613	231,097	201,613
Adjusted R^2	0.429	0.416	0.967	0.967	0.873	0.871	0.342	0.123

Internet Appendix

Figure A1. Bayesian Principal Components

Note: This figure depicts the factor loadings resulting from a Bayesian Principal Component Analysis (B-PCA) for the first two principal components (PC1 and PC2). The crude banking characteristics are denoted in red: ei01 - net interest margin, ei02 - lending minus deposits spread, ei03 - noninterest income to total income, ei04 - overhead costs to total assets, and ei05 - return on assets. The vectors represent the projected coordinate system for the banking characteristics.

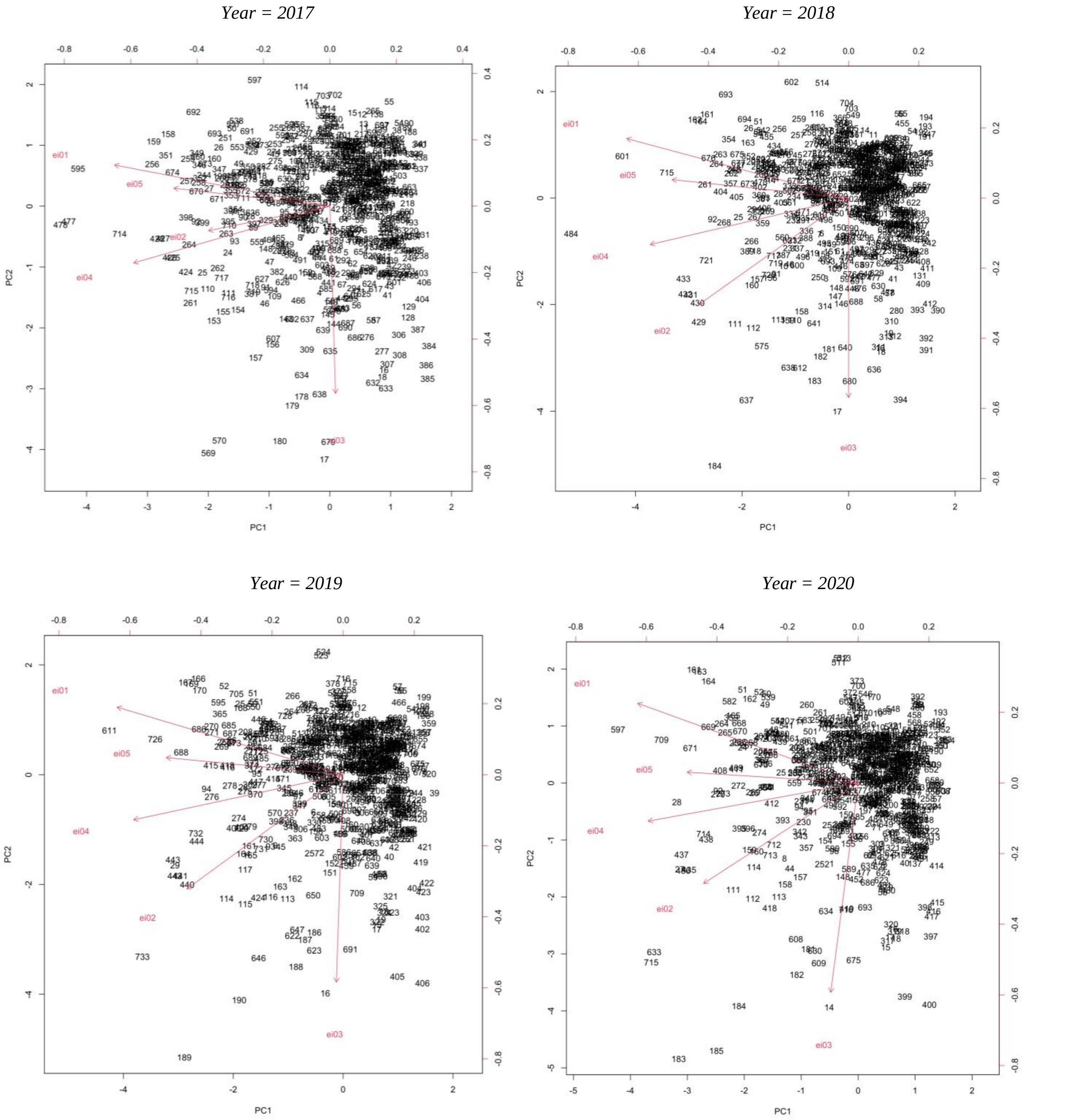


Figure A2. Banking System Efficiency: Pre-Crisis Average

Note: This figure plots the average the banking system efficiency (BSE) index from 2011 to 2019. BSE index is estimated as the first component using a Bayesian PCA using a bank's net interest margin, lending-deposits spread, non-interest income to total income, overhead costs to total assets, and return on assets. The darker (lighter) colors indicate a higher (lower) level of BSE.

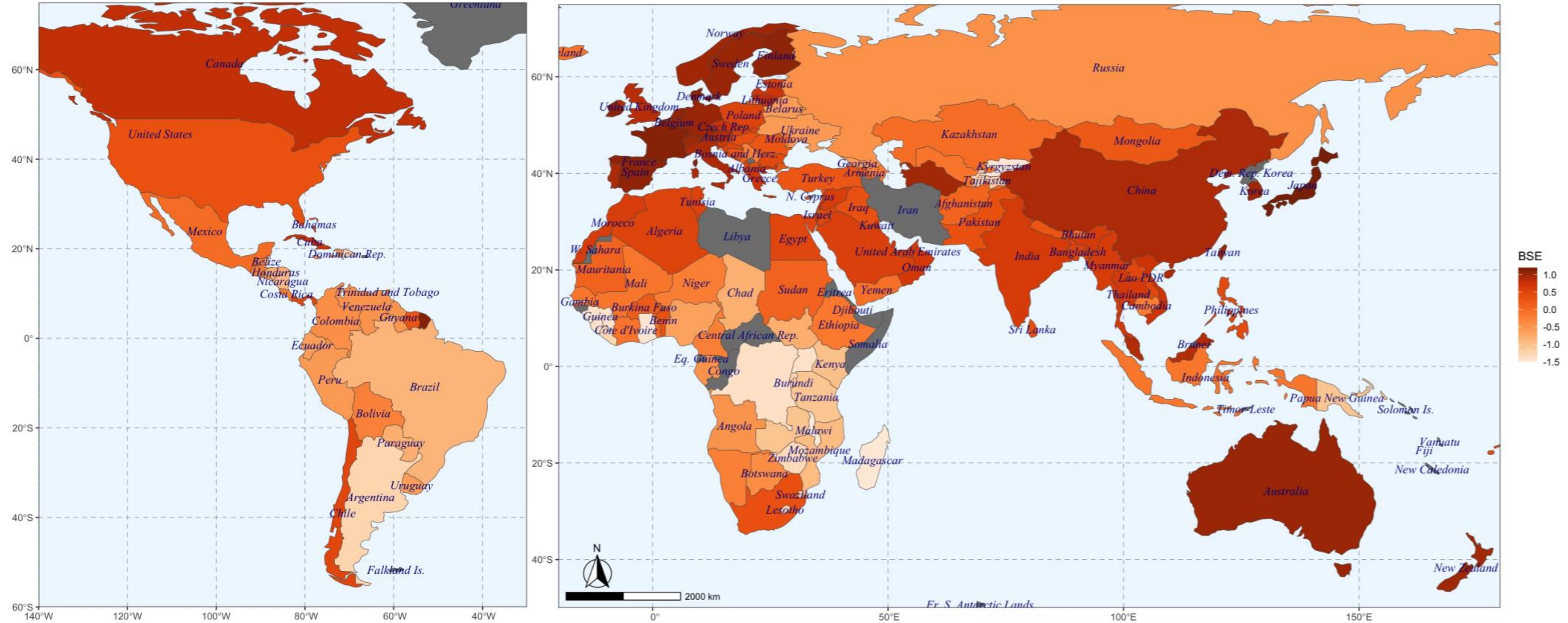
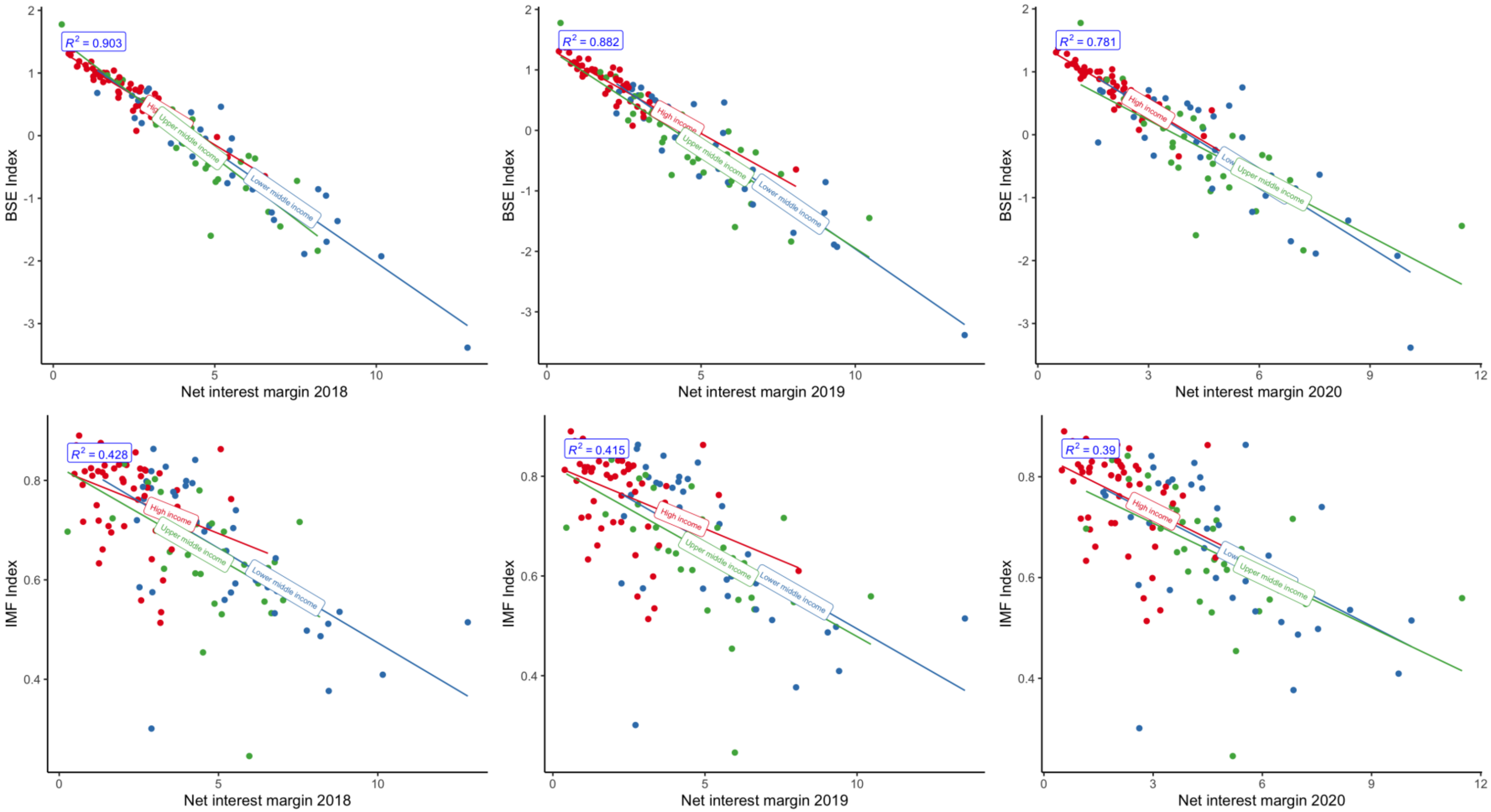


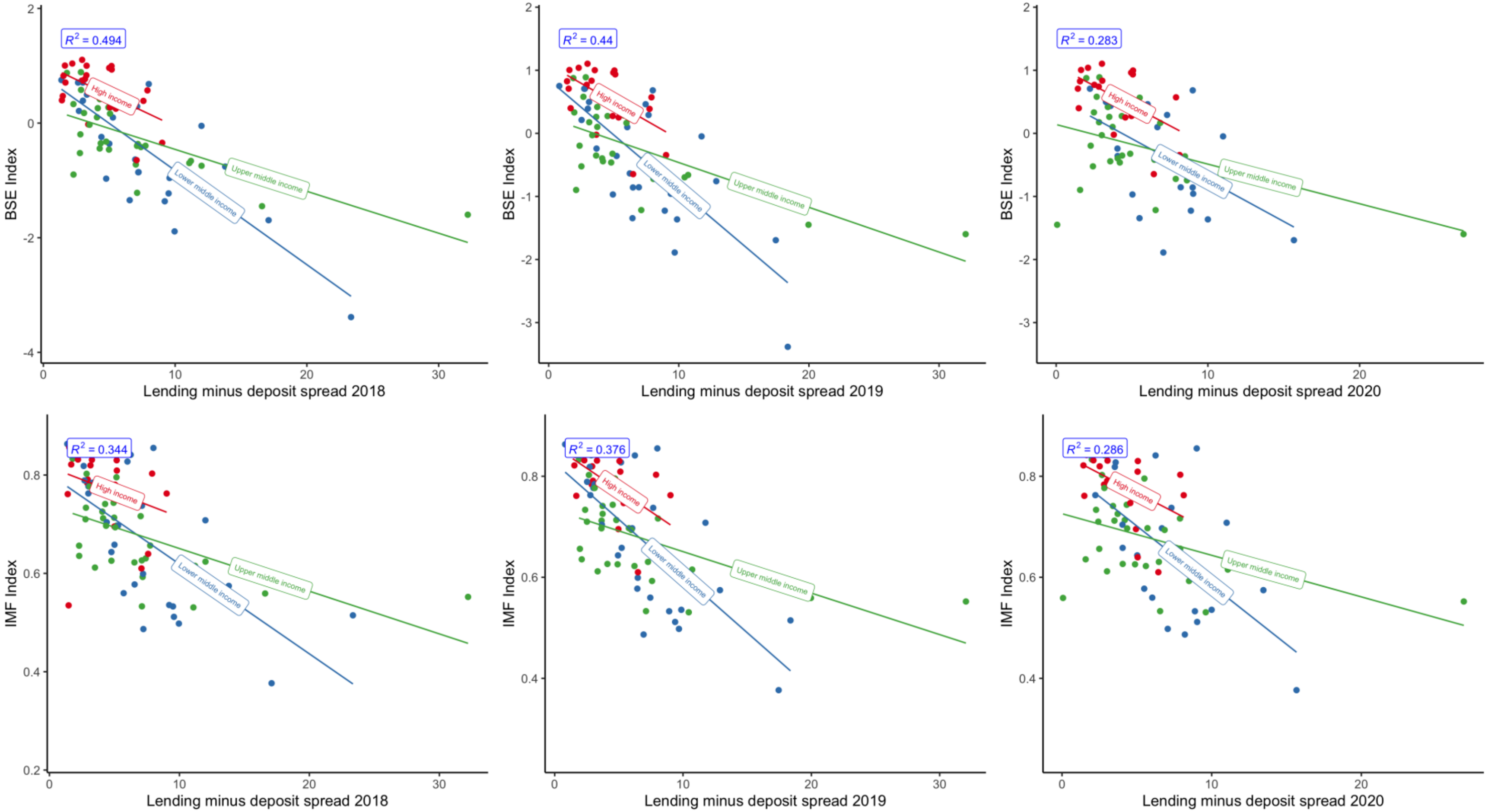
Figure A3: Out-of-Sample Performance: BSE Index versus IMF's FIE Index

Note: This figure compares the out-of-sample performance of the 2017 banking system efficiency (BSE) index and the 2017 IMF's FIE index over the period 2018 to 2020, evaluating their effectiveness in capturing key banking efficiency metrics: net interest margin, lending minus deposit spread, overhead costs to total assets, and return on assets. Both banking efficiency indices were constructed using data up to 2017. The underlying banking efficiency data were obtained from the World Bank.

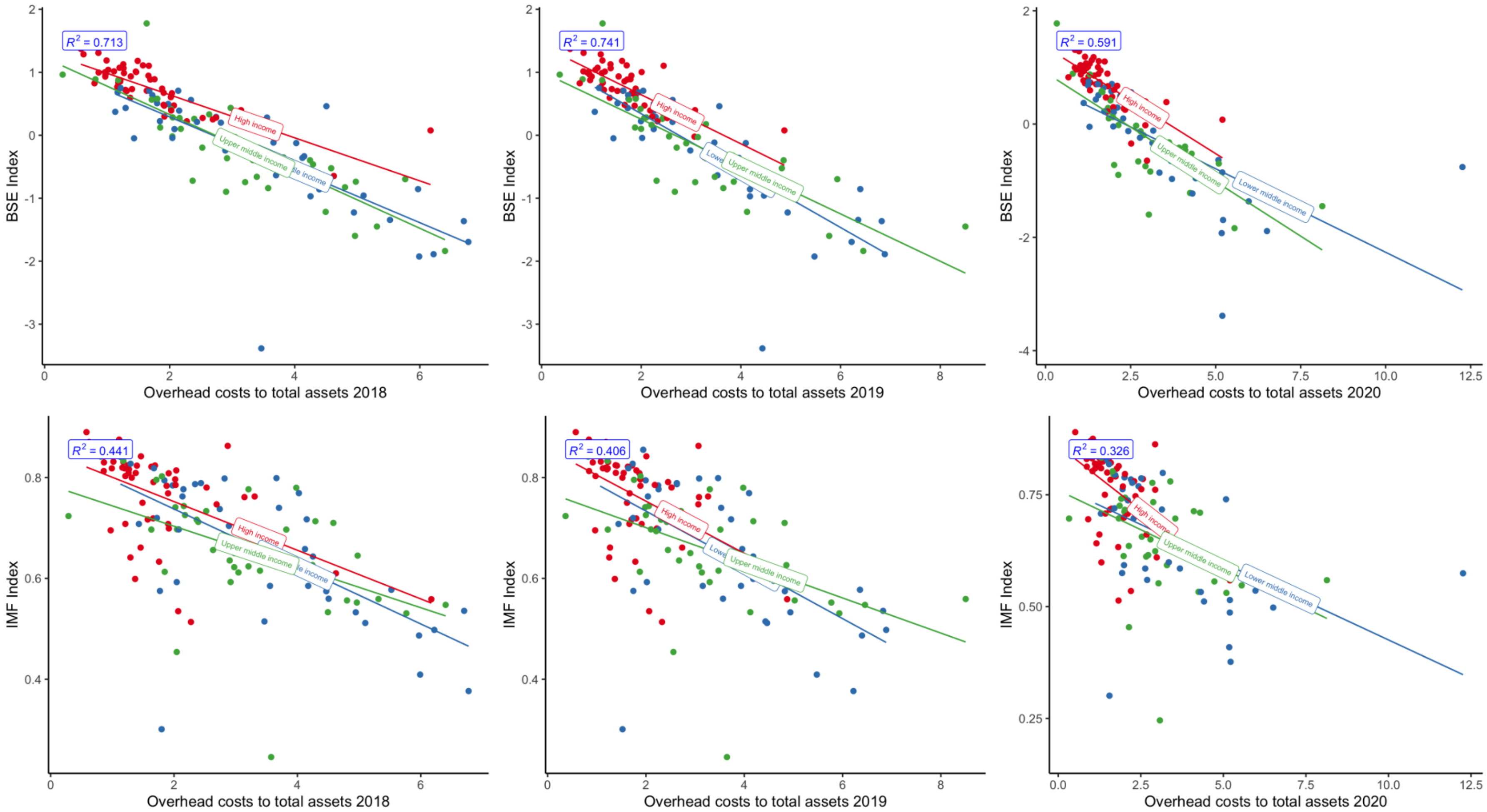
Panel A. Net Interest Margin



Panel B. Lending – Deposit Spread



Panel C. Overhead costs to total assets



Panel D. Bank Profitability (ROA)

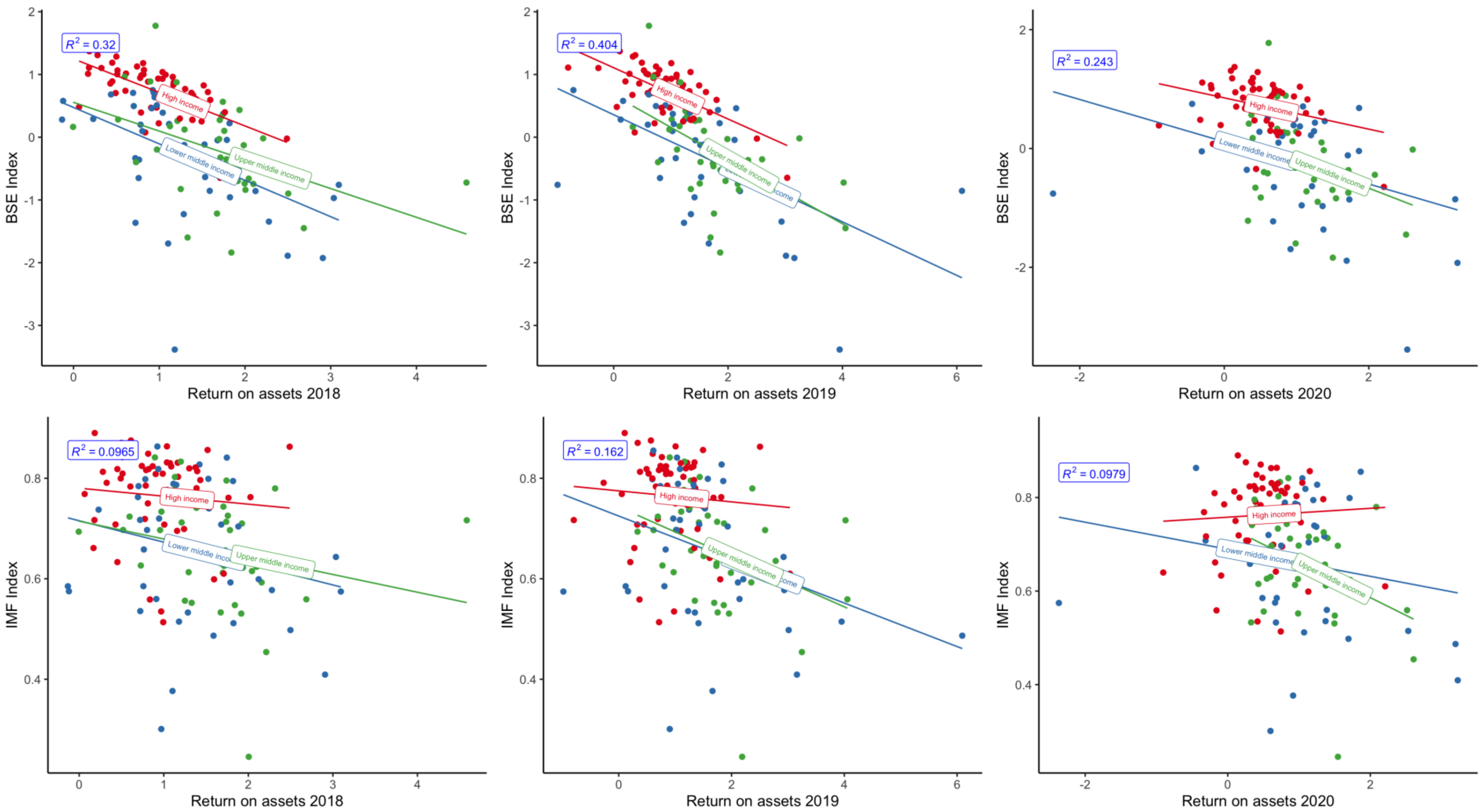


Table A1. Variable Description

Note: This table presents a detailed description and source of key variables.

Variable Name	Description	Source
BSE Index	The country-level index measuring the efficiency of the banking system.	Original Construction
CAPX/AT	The ratio of annual capital expenditure to book value of total assets at the beginning of the fiscal year.	Compustat
CF/TA	The ratio of annual cash flows to the book value of total assets at the beginning of the fiscal year.	Compustat
Ln Mkt Cap	The market capitalization in the natural logarithm at the end of the fiscal year.	Compustat
Tobin's Q	The ratio of the book value of assets plus the market value of common equity minus the book value of common equity and deferred taxes to the book value of assets as measured at the end of the fiscal year.	Compustat
Leverage	The ratio of the book value of debt divided by the book value of total assets at the beginning of the fiscal year.	Compustat
Ln(Employee)	Ln(Employee) is the national logarithm of the number of employees (in millions) at the fiscal year-end	Compustat
ROA	The ratio of operating income before depreciation to the book value of total assets at the beginning of the fiscal year.	Compustat
Cash Holding	The ratio of cash and short-term investments to the book value of total assets at the beginning of the fiscal year.	Compustat
GDP Growth	The yearly growth rate of GDP per capita.	IMF
Bank Credit/GDP	The ratio of total credit provided by banks to GDP per quarter.	Bank for International Settlements (BIS)
Credit to Household/GDP	The ratio of total credit provided to households to GDP per quarter.	Bank for International Settlements (BIS)
Credit to Corporation/GDP	The ratio of total credit provided to corporations to GDP per quarter.	Bank for International Settlements (BIS)

Table A2. Efficient Financial Institutions and Quantity of Credit Supply

Note: This table reports the summary of quarterly credit supply (in Panel A) and results of regressions of credits supply on banking system efficiency (BSE) controlling for quarterly GDP growth (In Panel B). BSE Index is the measure of efficiency in financial institutions. Bank Credit/GDP is the ratio of credit extended by domestic banks to the private non-financial sector scaled by the real GDP. We also report the borrowing statistics by households and corporations. The control variable vector includes the quarterly growth rate of the real GDP per capita. *Crisis* is an indicator variable with a value of 1 for the years 2020 and 2021, and zero otherwise. All regressions have country, year, and quarter fixed effects. *T*-statistics in parentheses are based on heteroskedasticity-corrected standard errors. Observations are the total number of country-quarter observations. Significance levels are indicated by asterisks: *** for 1%, ** for 5%, and * for 10%.

Panel A. Summary Statistics of Credit Supply

Variable	N	25th Pctl	Mean	Median	75th Pctl	Std Dev
Bank Credit/GDP	590	57.500	95.466	90.650	130.700	47.625
Credit to Household/GDP	590	35.200	62.241	59.750	87.900	31.206
Credit to Corporation/GDP	590	68.100	99.189	85.400	131.100	50.298

Panel B. Efficiency in Financial Intuitions and Credit Supply

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var =	Bank Credit/GDP		Credit to Household/GDP		Credit to Corporation/GDP	
BSE Index $_{t-1}$	-4.873	-9.319***	-1.996	-3.485***	-0.648	-4.233*
	(-1.228)	(-3.767)	(-1.134)	(-2.850)	(-0.246)	(-1.803)
BSE Index $_{t-1}$ × *Crisis*		4.239***		1.420***		3.418***
		(6.587)		(4.397)		(4.276)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	590	590	590	590	590	590
Adjusted R^2	0.990	0.991	0.994	0.995	0.988	0.988

Table A3. Broader Measures of Banking Systems Efficiency

Note: This table presents regression estimates of firm investment on country-level BSE indices based on a sample of Compustat Global firms from 2011 to 2021. The sample encompasses publicly listed firms from 55 countries. BSE Index represents the banking system efficiency. BSE^{8} index is the 1^{st} principal component of the Bayesian treatment of PCA, incorporating net interest margin, lending minus deposits spread, non-interest income to total income, overhead costs to total assets, bank's return on assets, bank's return on equity, banking sector concentration, and five bank asset concentration. BSE^{10} index include two additional characteristics that are related to bank stability: Bank credit to bank deposits and Liquid assets to deposits and short-term funding. All regressions include the baseline controls and restrictions. The crisis indicator variable assumes a value of 1 for the years 2020 and 2021 and zero otherwise. All accounting figures are denominated in US dollars, and all financial variables are winsorized at the 1^{st} and 99^{th} percentiles by country. Firm and year-fixed effects are included in all regressions. *T*-statistics in parentheses are derived from standard errors adjusted for country and year clustering. Observations represent the total number of firm-year observations. Significance levels are indicated by asterisks: *** for 1%, ** for 5%, and * for 10%.

Dependent Var = Capital	(1)	(2)	(3)	(4)
BSE $Broad^{8}_{t-1}$	-0.000	-0.001		
	(-0.089)	(-0.293)		
BSE $Broad^{8}_{t-1}$ × *Crisis*		0.005***		
		(3.791)		
BSE $Broad^{10}_{t-1}$			-0.002	-0.003
			(-0.923)	(-1.097)
BSE $Broad^{10}_{t-1}$ × *Crisis*				0.003**
				(2.464)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	230,603	230,603	229,103	229,103
Adjusted R^2	0.435	0.436	0.435	0.435

Table A4. IMF's FIE Index and Firm Investment

Note: This table presents regression estimates of yearly investment on IMF's financial institutions' efficiency (FIE) index based on a sample of Compustat Global firms from 2011 to 2021. The sample includes publicly listed firms from 55 countries. We exclude financial firms, firm-year observations with a non-positive book value of total assets or book value of common equity, or without accounting information that is required for key variable construction. Capital Investment is the ratio of annual capital expenditure to the book value of total assets at the beginning of the fiscal year. *Crisis* is an indicator variable with a value of 1 for years 2020 and 2021, zero otherwise. All regressions include the baseline controls and restrictions. All accounting figures are in US dollars and all financial variables are winsorized at 1 and 99 percentiles by country. All regressions include firm and year-fixed effects. *T*-statistics in parentheses are based on standard errors adjusted for country and year clustering. Observations are the total number of firm-year observations. ***, **, *, indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)
Dependent Var =	Capital Investment	
IMF FIE Index $_{t-1}$	0.044	0.044
	(1.669)	(1.662)
IMF FIE Index $_{t-1}$ × *Crisis*		0.004
		(0.286)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	231,097	231,097
Adjusted R^2	0.436	0.436

Table A5. Banking System Efficiency and Firm Capital Investment: Sub-Sample Analysis using Countries in the European Union

Note: This table presents regression estimates of yearly investment on country-level BSE indices based on a sample of Compustat Global firms from 2011 to 2021. The sample includes publicly listed firms from 55 countries. We exclude financial firms, firm-year observations with a non-positive book value of total assets or book value of common equity, or without accounting information that is required for key variable construction. Capital Investment is the ratio of annual capital expenditure to the book value of total assets at the beginning of the fiscal year. *Crisis* is an indicator variable with a value of 1 for the years 2020 and 2021, and zero otherwise. All regressions include the baseline controls and restrictions. All accounting figures are in US dollars and all financial variables are winsorized at 1 and 99 percentiles by country. All regressions include firm and year-fixed effects. *T*-statistics in parentheses are based on standard errors adjusted for country and year clustering. Observations are the total number of firm-year observations. ***, **, *, indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)
Dependent Var =		Capital Investment	
BSE Index $_{t-1}$	-0.009**	-0.007	-0.007
	(-2.478)	(-1.362)	(-1.486)
BSE Index $_{t-1}$ × *Crisis*	0.007***	0.005***	0.005***
	(4.924)	(4.689)	(4.688)
Controls	Yes	Yes	Yes
Firm FE	Yes	No	No
Country FE	No	Yes	Yes
Industry FE	No	No	Yes
Year FE	Yes	Yes	Yes
Observations	26,962	27,390	27,334
Adjusted R^2	0.451	0.0586	0.123

Table A6. Sub-sample Analysis: Capital Regulations

Note: This table presents regression estimates of yearly investment on country-level BSE indices based on a sample of Compustat Global firms from 2011 to 2021. The sample includes publicly listed firms from 55 countries. We exclude financial firms, firm-year observations with a non-positive book value of total assets or book value of common equity, or without accounting information that is required for key variable construction. Capital Investment is the ratio of annual capital expenditure to the book value of total assets at the beginning of the fiscal year. *Crisis* is an indicator variable with a value of 1 for the years 2020 and 2021, and zero otherwise. High capital stringency markets are those with overall capital stringency score of 7 or above. All regressions include the baseline controls and restrictions. All accounting figures are in US dollars and all financial variables are winsorized at 1 and 99 percentiles by country. All regressions include firm and year fixed effects. *T*-statistics in parentheses are based on standard errors adjusted for country and year clustering. Observations are the total number of firm-year observations. ***, **, *, indicate significance at the 1%, 5%, and 10% levels.

Dependent Var = Capital Investment	(1) High Capital Stringency	(2) Low Capital Stringency
BSE Index $_{t-1}$	0.002	0.004
	(1.358)	(0.974)
BSE Index $_{t-1}$ × *Crisis*	0.007*	0.007***
	(2.118)	(6.402)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	53,298	158,732
Adjusted R^2	0.363	0.467

Table A7. Robustness Tests: Access to Corporate Bond Market

Note: This table presents regression estimates of yearly investment on country-level BSE indices based on a sample of Compustat Global firms from 2011 to 2021. The sample includes publicly listed firms from 55 countries. We exclude financial firms, firm-year observations with a non-positive book value of total assets or book value of common equity, or without accounting information that is required for key variable construction. Capital Investment is the ratio of annual capital expenditure to the book value of total assets at the beginning of the fiscal year. *Crisis* is an indicator variable with a value of 1 for the years 2020 and 2021, and zero otherwise. Countries with and without private bond markets are identified using data compiled by Cihak *et al.* (2012). All regressions include the baseline controls and restrictions. All accounting figures are in U.S. dollars and all financial variables are winsorized at 1 and 99 percentiles by country. All regressions include firm and year fixed effects. *T*-statistics in parentheses are based on standard errors adjusted for country clustering. Observations are the total number of firm-year observations. ***, **, *, indicate significance at the 1%, 5%, and 10% levels.

Dependent Var = Capital Investment	(1)	(2)
BSE Index $_{t-1}$	0.003	0.002
	(0.742)	(0.362)
BSE Index $_{t-1}$ × Private Bond	-0.001	0.000
	(-0.269)	(0.016)
Private Bond	-0.001	-0.002
	(-0.099)	(-0.222)
BSE Index $_{t-1}$ × *Crisis*		0.006***
		(3.998)
BSE Index $_{t-1}$ × *Crisis* × Private Bond		0.000
		(0.019)
Crisis × Private Bond		-0.000
		(-0.100)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	231,097	231,097
Adjusted R^2	0.436	0.436

Table A8. Robustness Tests: Industry Vulnerability to Social Distancing

Note: This table presents regression estimates of yearly investment on country-level BSE indices based on a sample of Compustat Global firms from 2011 to 2021. The sample includes publicly listed firms from 55 countries. We exclude financial firms, firm-year observations with a non-positive book value of total assets or book value of common equity, or without accounting information that is required for key variable construction. Capital Investment is the ratio of annual capital expenditure to the book value of total assets at the beginning of the fiscal year. *Crisis* is an indicator variable with a value of 1 for the years 2020 and 2021, and zero otherwise. We use industry's vulnerability to social distancing measure from Koren and Pető (2020). *Non-resilient Industries* equal one for industry with KP score above median, zero otherwise. All regressions include the baseline controls and restrictions. All accounting figures are in US dollars and all financial variables are winsorized at 1 and 99 percentiles by country. All regressions include firm and year fixed effects. *T*-statistics in parentheses are based on standard errors adjusted for country and year clustering. Observations are the total number of firm-year observations. ***, **, *, indicate significance at the 1%, 5%, and 10% levels.

Dependent Var = Capital Investment	(1)	(2)
Non-resilient Industries × *Crisis*	-0.005**	-0.012***
	(-2.431)	(-3.681)
BSE Index $_{t-1}$		0.005
		(1.392)
BSE Index $_{t-1}$ × *Crisis*		0.000
		(0.062)
BSE Index $_{t-1}$ × Non-resilient Industries × *Crisis*		0.010***
		(3.449)
BSE Index $_{t-1}$ × Non-resilient Industries		-0.004
		(-1.715)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	106,279	106,236
Adjusted R^2	0.472	0.473

Appendix: First Order Conditions

The first order conditions (FOCs) are given by:

$$S_i: \quad p(S_i)\, A \cdot D_i + p'(S_i)[R_i D_i + \phi_D(Z) D_i + \beta\, V_N'(N')] = 0. \qquad \ldots\text{(A1)}$$

$$D_i: \quad p(S_i)\, R_i + p(S_i)[\phi_D(Z) + \phi_D'(Z) D_i] - p(S_i) r_D'(Z) D_i - \frac{\mu}{\kappa} = 0. \qquad \ldots\text{(A2)}$$

Using equation (2), in a symmetric equilibrium, we can derive the value of the bank as:

$$V(N) = \frac{\pi(N)}{1 - \beta\, p(S_i)}.$$

$$V = \pi(N) = E(N)\, [1 - \delta\, p(S)].$$

Appendix: B-PCA Methodology

The predictive density is obtained by marginalizing over the parameters such that:

$$p(\boldsymbol{y}|\mathbf{Y}) = \iiint P(\boldsymbol{y}|\boldsymbol{W}, \boldsymbol{\mu}, \tau)\, P(\boldsymbol{W}, \boldsymbol{\mu}, \tau|\mathbf{Y})\, d\boldsymbol{\mu}\, d\boldsymbol{W}\, d\tau.$$

Following Oba *et al.* (2003), we assume conjugate priors for τ and $\boldsymbol{\mu}$, and a hierarchical prior for $\boldsymbol{W}$, which is $p(\boldsymbol{W}|\tau, \alpha)$ that is parameterized by a hyperparameter $\alpha \in \mathbb{R}^K$. The priors are defined as follows:

$$p(\theta|\alpha) \equiv p(\boldsymbol{W}, \boldsymbol{\mu}, \tau|\alpha) = p(\boldsymbol{\mu} \mid \tau)p(\tau) \prod_{j=1}^{K} p\left(\boldsymbol{\omega_j} \mid \tau, \alpha_j\right),$$

where

$$p(\boldsymbol{\mu} \mid \tau) = \mathcal{N}\left(\boldsymbol{\mu}|\boldsymbol{\bar{\mu}_0}, \left(\gamma_{\mu_0}\tau\right)^{\mathbf{-1}} \boldsymbol{I_m}\right),$$
$$p\left(\boldsymbol{\omega_j} \mid \tau, \alpha_j\right) = \mathcal{N}\left(\boldsymbol{\omega_j}|\mathbf{0}, \left(\alpha_j\tau\right)^{\mathbf{-1}} \boldsymbol{I_m}\right),$$
$$p(\tau) = \mathcal{G}\left(\tau|\bar{\tau}_0, \gamma_{\tau_0}\right).$$

$\mathcal{G}(\tau|\bar{\tau}, \gamma_\tau)$ denotes a Gamma distribution with hyperparameters $\bar{\tau}$ and γ_τ:

$$\mathcal{G}(\tau|\bar{\tau}, \gamma_\tau) = \frac{(\gamma_\tau \bar{\tau}^{-1})^{\gamma_\tau}}{\Gamma(\gamma_\tau)} exp[-\gamma_\tau \bar{\tau}^{-1}\tau + (\gamma_\tau - 1)ln(\tau)],$$

where $\Gamma(\cdot)$ is a Gamma function. Following Oba *et al.*, the deterministic hyperparameters are set to $\gamma_{\mu_0} = \gamma_{\tau_0} = 10^{-10}$, $\boldsymbol{\bar{\mu}_0} = 0$, and $\bar{\tau}_0 = 1$, which corresponds to an almost non-informative prior.

Given the priors, the complete dataset **Y=(** $\boldsymbol{Y}^{obs}$, $\mathbf{Y}^{\text{miss}}$**)**, and the type-II maximum likelihood hyperparameter $\boldsymbol{\alpha}_{ML-II}$, we can obtain the posterior distribution $q(\boldsymbol{\theta}) = p(\boldsymbol{\theta}|\boldsymbol{Y}, \boldsymbol{\alpha}_{ML-II})$ by Bayesian estimation. However, we require $\mathbf{Y}^{\text{miss}}$, the missing values in the dataset **Y** to obtain $q(\boldsymbol{\theta})$.

Variational Bayes (VB) Algorithm

The posterior of the missing values is $q(\boldsymbol{Y}^{miss}) = p(\boldsymbol{Y}^{miss}|\boldsymbol{Y}^{obs}, \boldsymbol{\theta}_{\boldsymbol{true}})$, where $\boldsymbol{\theta}_{\boldsymbol{true}}$ is the true parameter set and $\boldsymbol{Y}^{obs}$ represents the observed values. The posterior given the $\boldsymbol{\theta}_{\boldsymbol{true}}$ is equivalent to the PC regression in (2). Given the posterior $q(\boldsymbol{\theta})$ instead of the true parameter $\boldsymbol{\theta}_{\boldsymbol{true}}$, the posterior distribution of the missing values is given by:

$$q(\boldsymbol{Y}^{miss}) = \int p(\boldsymbol{Y}^{miss}|\boldsymbol{Y}^{obs}, \boldsymbol{\theta})\, q(\boldsymbol{\theta}) d\boldsymbol{\theta},$$

which corresponds to the Bayesian PC regression.

We require $\boldsymbol{Y} = (\boldsymbol{Y}^{obs}, \boldsymbol{Y}^{miss})$ to estimate the posterior $q(\boldsymbol{\theta}) = p(\boldsymbol{\theta}|\boldsymbol{Y}, \boldsymbol{\alpha}_{ML-II})$ and $q(\boldsymbol{\theta})$ to estimate the posterior $q(\boldsymbol{Y}^{miss}) = \int p(\boldsymbol{Y}^{miss}|\boldsymbol{Y}^{obs}, \boldsymbol{\theta})\, q(\boldsymbol{\theta}) d\boldsymbol{\theta}$. Hence, we are required to obtain $q(\boldsymbol{\theta})$ and $q(\boldsymbol{Y}^{miss})$ simultaneously.

Employing an iterative algorithm, we derive the posterior distributions $q(\boldsymbol{\theta})$ and $q(\boldsymbol{y}^{miss})$. In accordance with the methodologies proposed by Attias (1999)Attias (1999) and Sato (2001)Sato (2001), we utilize the Variational Bayes (VB) algorithm for Bayesian estimation. The implementation of the algorithm is as follows:

1. Initialize the posterior distribution of $\boldsymbol{y}^{miss}$ by imputing each missing value with the mean of the corresponding banking characteristic.
2. Estimate the posterior distribution $q(\boldsymbol{\theta})$ of the parameter $\boldsymbol{\theta}$ using the sub-sample of data $\boldsymbol{y}^{obs}$ and the current posterior distribution of missing values, $q(\boldsymbol{y}^{miss})$.
3. Update the posterior distribution of the missing values, $q(\boldsymbol{y}^{miss})$, using the current posterior distribution $q(\boldsymbol{\theta})$.
4. Update the hyperparameter $\boldsymbol{\alpha}$ using the current $q(\boldsymbol{\theta})$ and current $q(\boldsymbol{y}^{miss})$.
5. Repeat steps 2 to 4 until convergence is achieved.

Utilizing the VB algorithm, we compute the posterior distributions $q(\boldsymbol{\theta})$ and $q(\boldsymbol{y}^{miss})$, which converge to the global optima. The missing values in the expression matrix are imputed to the expectation for the estimated posterior distribution: $\widehat{\boldsymbol{Y}^{miss}} = \int \boldsymbol{Y}^{miss}\ q(\boldsymbol{Y}^{miss})\ d\boldsymbol{Y}^{miss}$.