Efficient Financial Institutions, Economic Crises, and Firm Investment: International Evidence from the COVID-19 Pandemic*

Ruchith Dissanayake[a] and Yanhui Wu[b]

* For comments, we thank Renee Adams, Gil Aharoni, Jitendra Aswani, Jan Bena, Bo Bian, Alice Bonaime, Russell Davidson, Joseph Fan, Eliezer Fich, Mingze Gao, Harrison Hong, Alexandre Jeanneret, Hae Won Jung, Laura Lindsey, Mike Mao, Alexander Michaelides, Vikas Mehrotra, Konark Saxena, Harminder Singh, Jianfeng Shen, Ekaterina Volkova, Barry Williams, Yupana Wiwattanakantang, Zhaoxia Xu, and Hong Feng Zhang, conference participants at the China Finance Review International and China International Risk Forum, Econometric Society Africa Meeting, Econometric Society Australasian Meeting, Financial Markets and Corporate Governance Conference, FIRN Banking and Financial Stability Meeting, Queensland Corporate Finance Conference, and seminar participants at the Deakin University, University of Melbourne, University of New South Wales, and University of Queensland.

[a] Corresponding Author. QUT Business School. Email: r.dissanayake@qut.edu.au.
[b] QUT Business School - Economics and Finance. Email: sean.wu@qut.edu.au.

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Abstract

Utilizing a Bayesian treatment of principal component analysis, we develop time-varying country-level indices of banking efficiency. During the COVID-19 crisis, efficient banking systems extended more credit to the private non-financial sector compared to their inefficient counterparts. Firms operating in economies with efficient banks exhibit significantly lower sensitivity of capital investment to economic crises. This mitigating effect is particularly pronounced for firms that are more reliant on external financing. Notably, while efficient banks provide more credit during economic crises, they tend to allocate this credit disproportionately to firms with collateralizable assets rather than firms that are genuinely in need of financing.

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

JEL: D84, G31, G15

1. Introduction

The intricate relationship between banking institutions and economic growth has been a subject of intense debate among economists since the seminal work of Bagehot (1873). Bank financing has been consistently identified as a crucial catalyst for economic expansion, fostering both growth (King & Levine 1993; Levine & Zervos 1993; Berger & Sedunov 2017) and productivity (Krishnan *et al.* 2014). The significance 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 (GFC) (Campello *et al.* 2010; Duchin *et al.* 2010; Kahle & Stulz 2013; Giroud & Mueller 2017). Firms with greater financial flexibility are better equipped to navigate revenue shortfalls and maintain resilience in the face of economic shocks (Fahlenbrach *et al.* 2021). This paper delves into the impact of efficient banking institutions – those capable of facilitating the flow of funds to the private non-financial sector at a minimal intermediary cost while minimizing operational inefficiencies – on firm investment decisions amidst an economic crisis.

While the impact of banking institutions during financial crises has been extensively studied, as exemplified by Bernanke (1983)'s work on supply constraints for bank loans during the Great Depression and Chodorow-Reich (2013) analysis of the GFC, the role of banking efficiency amid non-financial economic crises remains largely unexplored. 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.[1] 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 quasi-natural experiment to evaluate the influence of banking efficiency on firm investment during economic crises.[2]

In contrast to traditional studies that rely on broad measures such as the ratio of private credit to GDP and stock market capitalization to proxy financial development, we focus on banking efficiency as a more nuanced metric.[3] These proxies, while capturing the size of the financial sector, overlook the crucial aspect of financial robustness. An unsustainable expansion of credit can jeopardize financial stability and erode the quality of investments

[1] We define non-financial economic crises as economic downturns that did not originate within the financial sector of the economy.
[2] According to the World Economic Outlook by the International Monetary Fund (IMF), global growth is expected to be -4.4 percent in 2020 and the recovery from the pandemic is likely long, uneven, and uncertain.
[3] See, for example, Rajan and Zingales (1998) and Levine and Zervos (1998).

(Aizenman *et al.* 2015).[4] Indeed, the importance of financial institutions extends beyond their mere size. Notable studies have demonstrated a positive association between bank efficiency and economic growth (Jayaratne & Strahan 1996; Levine 1998, 1999), highlighting the critical role of efficient financial intermediation in fostering economic activity. Kroszner and Strahan (2014), along with numerous other studies, further emphasize the significant effects of banking sector efficiency on overall economic performance. Therefore, our focus on banking efficiency provides a more refined and meaningful assessment of financial development.

The concept of banking efficiency encompasses the ability of banks to seamlessly channel funds to the private sector while minimizing intermediary costs and operational overheads. This multifaceted definition hinges on banks' ability to extend credit to the private sector at a low cost, optimize resource utilization, and operate within a competitive landscape. Despite its significance, the intricate relationship between efficient financial institutions (EFI) and corporate outcomes during economic crises has not been systematically examined across countries. One of the primary impediments to research progress in this domain is the lack of a comprehensive, consistently measured, and publicly available indicator of time-varying EFI.[5]

Adopting a systematic approach to measuring EFI at the country level, we propose a novel methodology that addresses the limitations of existing methods. Although principal component analysis (PCA) is widely employed in literature to extract latent factors such as efficiency, its standard application necessitates a complete set of observed data. However, several crucial banking efficiency characteristics are either missing or unobserved for certain international markets, necessitating a procedure that can effectively handle missing variables. Imputing, discarding, or splicing missing data can introduce significant biases in parameter estimation. For instance, within the sample from 2001 to 2020, 10.6% of country-level banking characteristics from the World Bank Global Financial Development Database are missing.[6] When employing conventional PCA, an entire country-year of data must be discarded even if a single characteristic is missing for a given year. This implies that, for the 2001-2020 sample, a substantial 51.5% of the data would need to be removed to apply conventional PCA.

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[4] For example, state-owned banks may channel credit to state-owned firms at the expense of credit to the dynamic private sector. Aizenman *et al.* (2015), for example, show that some of the Asian countries with large financial sectors are highly inefficient.

[5] 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.

[6] We use a single data source to gather banking data. It is difficult to create indices that can be compared across countries if we use multiple data sources for raw characteristics.

To address these challenges, we utilize a probabilistic PCA based on unsupervised machine learning literature (Bishop 1998; Tipping & Bishop 1999; Minka 2000; Oba *et al.* 2003). Specifically, our estimation method is based on the Bayesian treatment of the PCA (hereafter, B-PCA). The posterior distribution of the model parameters and the missing values are simultaneously estimated using a Variational Bayes repetitive algorithm.[7] In the spirit of Cihak *et al.* (2012), we use country-level bank's 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 our crude banking efficiency input variables for the baseline B-PCA.[8] We use data from over 150 countries and a 5-year rolling window to estimate the parameters. The weights of the PCA are adjusted on a rolling basis to avoid look-ahead bias. The first principal component is used as our novel country-level efficient financial institutions (EFI) index.[9]

The time-varying loadings (weighting matrix) derived from the B-PCA procedure reveal that the EFI index exhibits a negative correlation with bank net interest margin, lending minus deposits spread, bank overhead costs to total assets, and ROA. This implies that lower lending spreads, diminished bank operational costs, and reduced bank profitability all contribute to enhanced banking efficiency. Notably, the non-interest income to total income ratio has no discernible impact on the EFI index.

The first test involves a simulation experiment designed to assess the EFI index's robustness to data scarcity. We randomly dropped varying percentages of observations from the sample and compared the correlations between the EFI index and the first principal component (PC) obtained from the standard PCA. This procedure was repeated for 1000 iterations. Despite removing up to 15% of the data, the correlations remained consistently high, above 97%, indicating the EFI index's resilience to missing observations.

To evaluate the predictive power of the EFI index, we conducted an out-of-sample comparison against the well-established IMF's financial institution efficiency (FIE) index. We compare the correlation between the 2017 banking efficiency measures – constructed using data up to 2017 – and the raw banking characteristics – net interest margin, lending minus deposit spread, overhead costs to total assets, and bank profitability – in 2018, 2019, and 2020. For each raw characteristic, the EFI index consistently outperformed the IMF's FIE index in terms of both correlation and R^2, demonstrating its superior ability to predict future

[7] The algorithm is similar in sprit to expectation–maximization (EM) algorithm.
[8] High-interest margins arise due to inefficiencies in bank operating costs and market power (Wong 1997; Brock & Suarez 2000; Saunders & Schumacher 2000; Maudos & De Guevara 2004; Maudos & Solís 2009).
[9] We find similar results when the sample of countries in the Bayesian PCA is limited to countries listed on the Compustat Global universe.

performance based on historical data. Hence, the EFI index's robustness to data scarcity and its superior predictive power compared to the IMF's FIE index provide compelling evidence of its validity as a novel and effective measure of banking efficiency.

Our primary hypothesis posits that firms operating in economies endowed with efficient banking institutions exhibit a reduced sensitivity to demand downturns. This resilience stems from the crucial role of banks as a lifeline for corporate financing during times of panic. Deeper financial systems, as Caballero and Krishnamurthy (2001) observed, alleviate firm cash flow constraints and influence the cyclical composition of firm investment (Aghion *et al.* 2010). Indeed, disruptions in bank credit to firms during periods of economic turbulence can trigger harmful contractionary effects 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).[10] Access to external bank financing at favorable intermediary costs enhances a firm's financial adaptability in the face of economic crises. Moreover, banks' operational efficiency fosters firm confidence in the financial system during periods of economic turmoil. Consequently, efficient banking institutions can function as a "safety net" for corporations, mitigating the adverse impacts of crises on investment.

In a comprehensive examination of the hypothesis, we analyze a representative sample of publicly traded companies spanning 55 global markets. To capture the impact of the COVID-19 crisis, we construct a dummy variable that assumes a value of zero for the pre-crisis period (2018 and 2019) and one for the post-crisis period (2020 and 2021). To assess the role of banking efficiency during the crisis, we introduce an interaction term between the EFI index, and the crisis dummy variable.[11] Our findings reveal a significant positive interaction effect, corroborating the hypothesis that firms in economies with efficient banking institutions experience a less pronounced decline in investment during an economic crisis compared to those in economies with inefficient banking institutions.

To address concerns regarding the possibility that banking efficiency measures in the pre-crisis period may reflect country-level differences in crisis anticipation, we follow Duchin *et al.* (2010) and re-estimate the baseline specification using a two-year lagged EFI index. We continue to observe a positive interaction effect between the two-year lagged banking

[10] Although banks typically display procyclical lending behavior, they remain the main source of liquidity for most firms (Rajan 1994; Acharya & Steffen 2020a).
[11] This empirical framework enables us to include both time-varying country and firm characteristics as well as firm and time-fixed effects.

efficiency index and the COVID-19 crisis indicator. Furthermore, our results remain robust to the inclusion of additional macroeconomic variables, including interest rates, inflation rates, and unemployment rates, as well as regulatory factors pertaining to bank capital and stock market capitalization.

While the investment findings presented are compelling, they do not preclude the possibility that banking efficiency and firm investment are simultaneously influenced by a common, unobserved factor. To address this endogeneity concern, prior studies have leveraged cross-industry variations in financial dependence (Rajan & Zingales 1998; Cetorelli & Gambera 2001; Kroszner *et al.* 2007). In countries with advanced financial systems, industries with greater external financing needs tend to exhibit faster growth rates compared to those that can self-finance their investments. Utilizing this approach, we test the hypothesis that banking efficiency has a more pronounced impact on firm investment during an economic crisis in sectors that are more reliant on external financing. Given that banks serve as a firm's primary source of liquidity during crises, we hypothesize that the effect of banking efficiency is more pronounced in sectors with higher external financing dependencies. Adopting Rajan and Zingales (1998) methodology, we identify sectors with greater external financing needs. Industries with external financing dependencies above the within-country median are classified as high external finance-dependent industries. Our results reveal an asymmetric effect of banking efficiency on sectors with higher external financing dependencies, thus corroborating the external financing mechanism.[12]

Leveraging survey data from the World Bank Enterprise Surveys, we delve into the intricacies of the external financing hypothesis, examining the proportion of firms utilizing bank loans to fund investment activities. The influence of banking efficiency is anticipated to be more pronounced in countries where a higher proportion of firms depend on bank loans for investment purposes. To pinpoint countries with varying levels of bank loan dependence, we devise an annual ranking based on the proportion of firms using bank loans to finance investment and subsequently divide the sample along the median. Our analysis unveils that EFI exerts a significant impact on firm-level investment during crises in countries with a high prevalence of bank financing for investment. Conversely, EFI exhibits no discernible impact on investment in low bank financing countries. This compelling observation highlights the

[12] In addition, 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.

pivotal role played by banking efficiency for firms that heavily rely on bank loans to finance their capital investment endeavors.

Delving into the lending behavior of efficient banks during economic crises, we investigate whether they prioritize firms with the ability to finance or those in need of financing. Firms endowed with greater financing capabilities are defined as those operating in sectors with higher collateral assets, which can be pledged as security for bank loans. Given the limited debt capacity of firms, collateral serves as a crucial mechanism to secure loans, thereby mitigating agency costs and contractual frictions arising from asymmetric information (Hart & Moore 1994; Kiyotaki & Moore 1997). Additionally, collateral alleviates lending inefficiencies, such as instances where local relationship banks, facing competition from distant transactional lenders, reject marginally profitable projects with positive net present value (Inderst & Mueller 2007).

To identify firms with higher collateral assets, we employ two proxies: the firm's tangible assets to total assets ratio and the cyclicality of durable goods industry sales. Firms with lower tangible asset ratios are more likely to face restricted credit access when banks reassess risk (Berger *et al.* 1996). Moreover, firms with a substantial proportion of intangible assets, which are often difficult to quantify, may encounter challenges in raising funds from external sources such as banking institutions (Kroszner *et al.* 2007). To distinguish firms based on tangibility levels, we construct an annual ranking based on the tangibility ratio and subsequently divide the sample along the median.

The second proxy, based on the cyclicality of durable goods industry sales, stems from the observation that collateralized borrowing declines when assets in receivership are unlikely to be allocated to their first-best alternative users, which are likely to be firms within the same industry (Shleifer & Vishny 1992). Since durable goods producers are highly sensitive to business cycles, negative demand shocks are likely to affect all potential alternative users of a durable producer's assets, consequently reducing tangibility (Almeida & Campello 2007). To differentiate firms based on durability levels, we classify consumption good producers into durable and non-durable categories based on industry input-output accounts, as per Gomes *et al.* (2009).

Our empirical investigation demonstrates that during an economic crisis, the impact of banking efficiency on firm investment is particularly acute for companies with a higher tangibility ratio. Additionally, we observe that the banking effect is more pronounced for firms operating in the nondurable goods sector. These findings suggest that banks prioritize lending to firms with a higher likelihood of loan repayment, underscoring the role of collateral in credit allocation decisions.

The evaluation of financial constraints poses a significant challenge in empirical research, as each measure employed inevitably entails inherent limitations. Drawing upon the work of Erel *et al.* (2015), we adopt two alternative measures that can be effectively constructed within an international context. The extant literature suggests that firms grappling with financial constraints exhibit a heightened sensitivity of cash flow to both investment and cash holdings (Fazzari *et al.* 1988; Almeida & Campello 2007). Encompassing both measures, we examine the extent to which efficient banks prioritize lending to financially constrained firms. Our findings reveal no compelling evidence to support the notion that efficient banks allocate a larger share of their lending to financially constrained firms during periods of economic downturn.

To discern whether efficient banks served as a safety net for firms during the COVID-19 crisis, we conduct a sensitivity analysis based on firm exposure to the pandemic's adverse effects. If this hypothesis holds true, we anticipate a more pronounced impact of banking efficiency on investment for firms that bore the brunt of the crisis's disruptions. We employ three metrics to gauge firm exposure: the prevalence of new COVID-19 cases, the extent of governmental economic support as captured by the economic support indexes from the Oxford COVID-19 Government Response Tracker, and the level of resilience to social distancing measures, as determined by the affected share measure developed by Koren and Pető (2020). Our findings reveal that the positive relationship between banking efficiency and investment is significantly stronger for firms operating in markets with high COVID exposure, limited government support, and industries exhibiting low social distancing resilience.

2. Literature Review and Hypothesis Development

2.1. Relevant Literature and Contribution

This paper delves into the intricate relationship between financial slack and the propagation of economic shocks, making a significant contribution to the existing body of knowledge. A compelling body of research has demonstrated that firms with more fragile balance sheets were disproportionately affected by the repercussions of the GFC (Duchin *et al.* 2010; Kahle & Stulz 2013; Giroud & Mueller 2017). It has been established that the sensitivity of firm performance to the financial crisis is contingent upon the severity of credit constraints (Campello *et al.* 2010). Levine *et al.* (2016) provide compelling evidence that the detrimental impact of a banking crisis on firm performance is mitigated for those entities with the ability to issue equity at a lower cost. Fahlenbrach *et al.* (2021) further reinforce the notion that firms possessing greater financial flexibility were better equipped to navigate the revenue shortfalls induced by the COVID-19 shock. Our study extends this line of inquiry by documenting that the pandemic-induced decline in capital investment was less pronounced for firms operating in countries with robust banking systems.

In the dynamic realm of COVID-19 crisis research, we attempt to make a significant contribution to the ongoing discourse. The burgeoning body of literature has examined the far-reaching impact of COVID-19 on various financial indicators, including stock returns (Albuquerque *et al.* 2020; Ramelli & Wagner 2020) and corporate bond liquidity (O'Hara & Zhou 2021). Ding *et al.* (2021) demonstrate that firms possessing a more robust pre-pandemic financial standing experienced a less severe decline in stock returns. Additionally, firm resilience in the face of stringent social distancing measures has also been identified as a crucial factor influencing stock returns (Papanikolaou & Schmidt 2022; Pagano *et al.* 2023). Furthermore, the literature has delved into the impact of COVID-19 on credit line drawdowns (Acharya & Steffen 2020b) and the withdrawal of funds from pre-existing credit lines (Li *et al.* 2020). We contribute to this literature by presenting compelling evidence that efficiently functioning banking institutions played a pivotal role in providing a lifeline of credit to the private sector, effectively mitigating the decline in corporate investment during the COVID-19 crisis. The positive impact of efficient banks is particularly pronounced in countries characterized by less government economic support and industries less capable of adapting to the challenges imposed by social distancing measures.

Our study contributes to the literature evaluating the efficiency of banks across different countries. A branch of the literature utilizes banking inputs (e.g., bank capital and labor) and outputs (e.g., total loans, total deposits, and number of branches) to calculate banking efficiency scores. Due to data limitations, most such studies focus on banks from a limited number of developed nations (e.g., Berg *et al.* 1993; Allen & Rai 1996; Pastor *et al.* 1997; Maudos *et al.* 2002; Kwan 2003). These measures of banking efficiency are also highly sensitive to the model specification. To encompass various aspects of financial development, Cihak *et al.* (2012) propose cross-country cross-time crude variables. We employ a Bayesian approach to principal component analysis (PCA) on these crude variables to construct cross-country time-varying indexes of efficiency in financial institutions. Our time-varying indexes encompass over 150 countries, spanning both developed and emerging markets.[13]

2.2. Hypothesis Development

Empirical research has delved into the intricate mechanisms by which bank credit disruptions influence corporate finance decisions during financial crises (e.g., Bernanke 1983; Chodorow-Reich 2013). Abrupt contractions in bank credit availability can cause detrimental economic consequences, dampening firm investment and employment (Kroszner *et al.* 2007; Kroszner & Strahan 2014). However, the adverse impact of economic downturns on investment can be mitigated by firms' access to bank credit, which serves as the primary source of external financing for corporations during turbulent market conditions. Building upon this premise, we posit the following hypothesis:

Hypothesis 1: *The sensitivity of investment to economic crises is comparatively lower for firms operating in economies with efficient banking systems compared to firms in economies characterized by inefficient banking institutions.*

Our first hypothesis posits that firms in economies with efficient banking institutions exhibit greater resilience in the face of economic crises, translating into a reduced sensitivity of investment to economic downturns. In contrast, firms operating 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 fluctuations.

This relationship between banking efficiency and investment is likely to be more pronounced for firms that are heavily reliant on external financing sources. Rajan and Zingales (1998) aptly posit that the development of financial institutions can alleviate credit constraints, enabling sectors with a high external financing dependence to achieve accelerated growth. Kroszner *et al.* (2007) further corroborate this view by demonstrating an asymmetric impact of financial development on sectors with substantial external financing needs during periods of banking crises.

Economic downturns often compel corporate managers to curtail investment activities due to the prevailing uncertainty and heightened risk aversion. However, firms that can access credit at reduced intermediary costs during such crises are less likely to implement drastic

[13] The country-level EFI indexes are available to download from the corresponding author's website.

investment cuts. Enhanced banking efficiency can play a crucial role in mitigating the adverse effects of crises on investment, particularly for firms that heavily depend on external financing. This is because banks often serve as the primary source of liquidity for firms during economic turmoil (Li *et al.* 2020). Consequently, we anticipate that banking efficiency will disproportionately benefit firms in sectors with a greater dependence on external financing during an economic crisis. Grounded in the aforementioned reasoning, we propose the following hypothesis:

Hypothesis 2: *During periods of economic crisis, the positive effect of banking efficiency on investment is greater for firms with a higher degree of external financing dependence.*

While banking efficiency plays a crucial role in alleviating liquidity constraints by providing access to external financing, the ability to secure debt agreements is limited to a select group of firms with collateral. This highlights the fundamental role of collateral in most debt agreements. Tangible asset values serve as a pivotal determinant in expanding debt capacity and facilitating investment. Collateral acts as a mitigating factor against ex-ante information asymmetries between firms and lenders, thereby curbing adverse selection and credit rationing issues (Stiglitz & Weiss 1981). Collateralization additionally alleviates moral hazard concerns (Boot *et al.* 1991; Aghion & Bolton 1997; Holmstrom & Tirole 1997) and contractual enforcement difficulties (Albuquerque & Hopenhayn 2004; Cooley *et al.* 2004).

Collateral assets play a crucial role in shaping the investment decisions of firms (Gan 2007; Chaney *et al.* 2012). As a prerequisite for securing bank loans, firms must pledge assets as collateral (Hart & Moore 1994; Kiyotaki & Moore 1997). Kroszner *et al.* (2007), for instance, demonstrate that firms with a higher proportion of intangible assets face greater challenges in accessing external financing from sources such as banking institutions. Collateral-rich firms are better equipped to weather the adverse effects of crises by renegotiating bank loans. In light of this, we propose the following hypothesis:

Hypothesis 3: *During an economic crisis, the positive impact of banking efficiency on investment is amplified for those firms with a higher proportion of collateral assets*.

The remainder of this paper will delve into the empirical examination of each hypothesis using our global sample.

3. Data

3.1. Crude Banking Efficiency Characteristics

The scarcity of comprehensive and comparable data across nations often constrains international studies to rely on rudimentary measures of financial development. The cross-country banking literature has identified several crude characteristics associated with efficient financial institutions. Cihak *et al.* (2012) posit that the net interest margin, lending-deposit spread, non-interest income to total income ratio, overhead costs as a percentage of total assets, and profitability metrics (return on assets and return on equity) are inversely related to bank efficiency. We utilize the World Bank Group's Global Financial Development Database to gather these banking characteristics. 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 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 return on assets (ROA) metric captures commercial banks' after-tax net income to yearly averaged total assets.

3.2. 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 U.S. dollars.

Capital investment is quantified as the ratio of annual capital expenditure (CAPX) to the book value of total assets (AT) at the beginning of the fiscal year. Total investment is calculated as the ratio of annual total investment (the sum of capital expenditure and R&D 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.

3.3. Credit Supply Data

We use data from the Bank for International Settlements (BIS) to examine the credit supply by financial institutions during the COVID-19 crisis. BIS compiles country-level series by combining data from several sources, such as the financial accounts by institutional sector, the balance sheets of domestic banks, international banking statistics, and the balance sheets of non-bank financial institutions.

We use quarterly data on the bank credit to the private non-financial sector, which includes non-financial corporations, households, and non-profit institutions serving households as defined in the System of National Accounts 2008. In addition, we use BIS data for the total credit borrowed by households and corporations.

4. The Efficient Financial Institutions (EFI) Indexes

We propose a systematic approach to constructing country-level indexes of financial institutions' efficiency. 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.[14]

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

4.1. Methodology

4.1.1. 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 characteristics, where D is the number of characteristics and N is the number of economies. The (i, j) 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 $i = 1, \ldots, D$. 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 $x_l = \left(\frac{\omega_l}{\lambda_l}\right)^T \boldsymbol{y}$.

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:

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

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 $p(\boldsymbol{y}_i|\boldsymbol{\omega_l}) = \mathcal{N}(x_l\boldsymbol{\omega_l}, (1/\tau)\ I_D)$.

4.1.2. *Missing Data*

Consider a dataset $\mathbf{Y}$ where a subset of values, denoted as $\boldsymbol{y}^{\boldsymbol{miss}}$, 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 $\boldsymbol{\omega_1}^{obs}, \ldots, \boldsymbol{\omega_K}^{obs}$. The least-square solution is given by:

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

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

$$\boldsymbol{y}^{miss} = \boldsymbol{W}^{miss}\boldsymbol{x}. \tag{2}$$

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

4.1.3. *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:

$$p(\boldsymbol{\theta}, \boldsymbol{X}|\boldsymbol{Y}) \propto p(\boldsymbol{Y}, \boldsymbol{X}|\boldsymbol{\theta})\, p(\boldsymbol{\theta}). \tag{3}$$

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:

$$\ln p(\boldsymbol{y} \mid \boldsymbol{\theta}) = -\frac{\tau}{2}\|\boldsymbol{y} - \boldsymbol{W}\boldsymbol{x} - \boldsymbol{\mu}\|^2 - \frac{\tau}{2}\|\boldsymbol{x}\|^2 + \frac{D}{2}\ln\tau + \frac{K+D}{2}\ln 2\pi, \tag{4}$$

where $\boldsymbol{\theta} \equiv \{\boldsymbol{W}, \boldsymbol{\mu}, \tau\}$ is the parameter set. The predictive density is obtained by marginalizing over the parameters such that:

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

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 $\alpha \in \mathbb{R}^K$. 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 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 $\mathbf{Y}$ to obtain $q(\boldsymbol{\theta})$.

4.1.4. *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) and 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: $\widehat{\boldsymbol{Y}^{miss}} = \int \boldsymbol{Y}^{miss}\ q(\boldsymbol{Y}^{miss})\ d\boldsymbol{Y}^{miss}$.

4.2. Index Construction

4.2.1. Estimating EFI Indexes

We employ five financial indicators to construct our country-level EFI index: net interest margin (NIM), lending-deposits spread, non-interest income to total income ratio, overhead costs as a percentage of total assets, and return on assets (ROA). 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 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. We adopt B-PC1 as our measure of EFI. We are able to construct the index for 163, 162, 162, and 151 countries for the years 2017, 2018, 2019, and 2020, respectively.

Figure 1 depicts the B-PC1 plotted against the second principal component (B-PC2). The arrows illustrate the loadings of each crude banking characteristic input on the B-PC1. The x-axis (horizontal axis) represents the crucial dimension for the B-PC1. NIM, lending-deposit spread, overhead costs to total assets, and ROA all load negatively for B-PC1. The loading arrows for NIM, overhead costs to total assets, and ROA characteristics are significantly longer, highlighting the importance of these inputs for banking efficiency. The negative association between the banking characteristics and the first principal component implies that higher values of B-PC1 are associated with enhanced overall banking efficiency. On average, B-PC1 captures approximately 45% of the variation in the crude banking efficiency measures.

[Please Insert Figure 1 Here]

4.2.2. Cross-Country Disparities in Banking Efficiency

The EFI index reveals striking heterogeneity in banking efficiency across countries, even within geographically proximate regions.[15] 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-EFI groups. High-income countries with consistently high EFI Index scores include Japan, France, Belgium, Denmark, Finland, and Luxembourg. Among low-income

[15] For a visual, Figure A1 in the Appendix plots a world map with the EFI Indexes in 2018 (pre-COVID-19 crisis). The darker colors indicate higher EFI index.

countries, Lebanon, Vietnam, India, Syria, Morocco, and Tunisia consistently exhibit generally high EFI Index scores.

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

[Please Insert Figure 2 Here]

4.3. Validating the Measure

4.3.1. Simulation-Based Validation

The inherent latent nature of banking 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 bank efficiency, we conduct a comprehensive simulation-based validation exercise. This simulation aims to evaluate how closely our EFI index aligns with a true index that would be constructed if we had access to a complete dataset with no missing observations.

We utilize the observed dataset $\boldsymbol{y}^{obs}$ comprising the crude efficiency characteristics of net interest margin, lending-minus-deposits spread, non-interest income to total income, overhead costs to total assets, and return on assets. 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. *EFI Index Estimation:* For each missing data scenario, we apply the Bayesian PCA method to the incomplete dataset and calculate the corresponding EFI index.
4. *Correlation Analysis:* We compute the correlation coefficient between the EFI index obtained from the Bayesian PCA 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 2 presents the mean and 95% confidence interval for the correlation between the EFI index and the true index across all simulation runs. The average correlation exhibits a monotonic decreasing trend as the percentage of missing values increases. This observation is intuitive, as a higher proportion of missing data implies a reduced amount of information available for the EFI index to accurately capture the underlying true index. Nonetheless, even for the simulation with 15% of missing data, the correlation between the EFI index and the true index remains remarkably high, exceeding 0.97. This finding underscores the robustness of our proposed method under various missing data scenarios, highlighting its potential as a reliable tool for economic analysis in the presence of incomplete information.

[Please Insert Table 1 Here]

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

To evaluate the out-of-sample predictive power of the EFI index relative to the IMF's financial institutions efficiency index (FIE), we conduct a comparative analysis of their correlations with raw banking characteristics, including NIM, lending minus deposit spread, overhead costs to total assets, and bank profitability. This comparison is performed using data from 2018, 2019, and 2020.

To ensure clean identification, we employ banking efficiency indexes constructed solely with data up to 2017. Since we use a rolling window for estimation, the 2017 EFI index utilizes information from 2013 to 2017. Conversely, the IMF's FIE 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, which is based on data up to 2017.

Figure 3 depicts the correlation between the 2017 banking efficiency index and raw banking efficiency characteristics for varying income levels in 2018, 2019, and 2020. Additionally, the R^2, the coefficient of determination, is reported for each test. Panel A reveals that the R^2 values for the EFI index are nearly twice as high as those for the IMF’s FIE index. The R^2 between the 2017 EFI index and the 2018 NIM is 0.90, while the R^2 between the 2017 IMF’s index and the 2018 NIM is 0.49. The outperformance of the EFI index over the IMF’s index persists in 2019 and 2020. Panel B demonstrates that the correlation with the lending minus deposit spread is substantially higher for the EFI index than for the IMF's FIE index. However, for both indexes, the correlation is low for low-income countries.

Panel C illustrates that the EFI index exhibits a significantly higher out-of-sample correlation with banking overhead costs compared to the IMF's index. The R^2 between the 2017 EFI index and the 2018 banking overhead costs is 0.74, while the R^2 between the 2017 IMF’s index and the 2018 banking overhead costs is 0.51. The R^2 values for the EFI index are considerably higher in 2019 and 2020 than those for the IMF's index.

The out-of-sample fit between banking efficiency and ROA is also superior for the EFI index compared to the IMF's FIE index. A weak relationship is observed between the IMF's FIE index and out-of-sample bank ROA for both high-income and low-income countries. Overall, the EFI index demonstrates a significantly better out-of-sample fit with raw measures for bank lending costs, operating costs, and profitability.

[Please Insert Figure 3 Here]

5. Banking Efficiency and Firm Investment

Employing the EFI indexes, we conduct an empirical examination of the hypothesized relationship between banking efficiency and firm investment behavior during an economic crisis.

5.1. Sample Statistics

Table 1 presents a summary of the key statistics for our cross-national dataset, encompassing 55 countries sampled between 2018 and 2021. All financial variables are winsorized at the 1st and 99th percentile levels to mitigate the impact of outliers.

EFI 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 EFI index.

[Please Insert Table 2 Here]

5.2. The Baseline Model: Banking Efficiency and Investment

To delve into the intricate relationship between banking efficiency and investment, we commence by estimating the following baseline model:

$$Inv_{i,c,t} = \alpha_i + \tau_t + \beta_1 EFI_{c,t-1} + \beta_2 EFI_{c,t-1} \cdot crisis + \beta_3 \mathrm{X}_{i,t-1} + \varepsilon_{i,t}\ , \quad \cdots (5)$$

where i indexes' firms, c indexes countries. α_i and τ_t's are firm and time fixed effects. $Inv_{i,t}$ is the investment (capital investment and total investment) by firm i in country c in year t. The central variable of interest is the interaction term between the EFI 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 countries with more efficient banking institutions exhibit a reduced decline in investment compared to those in countries with less efficient banking institutions. This finding would underscore the crucial role of banking efficiency in mitigating the adverse effects of crises on investment behavior.

Table 2 presents the findings of estimating equation (5). Models (1) and (3) demonstrate the average impact of financial institutions' efficiency on total investment and capital investment, respectively. In each model, the EFI index coefficient is positive and statistically significant. This implies that, on average, financial institutions' efficiency has a beneficial effect on firm investment. The firm's growth prospects, proxied by Tobin's Q, are also positively correlated with investment, as predicted by the classical investment model. The real GDP growth rate, which measures growth opportunities at the country level, is also positively correlated with investment, as anticipated.

Models (2) and (4) examine the interaction effect of financial institutions' efficiency and the COVID-19 crisis on firm investment. The coefficients on the interaction terms are positive and statistically significant. Overall, our findings strongly support hypothesis 1, which states that the sensitivity of investment to an economic crisis is lower for firms operating in economies with efficient banking institutions than for firms operating in economies with inefficient banking institutions.

[Please Insert Table 3 Here]

To visually depict the disparity in capital investment between firms in high EFI and low EFI countries, we present a figure showcasing the difference in investment levels. For simplicity, we classify any country with an EFI score exceeding the median in 2018 as a High EFI country, while those below the median are categorized as Low EFI countries.

In the first stage, to control for investment opportunities, we estimate the regression in (5) excluding $EFI_{c,t-1}$ and $EFI_{c,t-1} \cdot crisis$ terms. This step allows us to isolate the effect of EFI on investment while controlling for investment opportunities. In the second stage, we estimate the average and 99 percent confidence intervals for Low EFI countries and High EFI countries.

Figure 5 illustrates the averages and confidence intervals for Low EFI countries and High EFI countries before and after the COVID-19 shock. Prior to the shock, firms in both low and high EFI countries exhibited parallel investment trends. However, following the demand shock, the average investment declined for both Low EFI and High EFI countries. Notably, firms in Low EFI countries experienced a significantly greater drop in investment compared to their counterparts in High EFI countries. This differential impact underscores the heightened vulnerability of firms in low EFI countries to economic shocks.

[Please Insert Figure 4 Here]

5.3. Broader and Narrower Measures of Banking Efficiency

To delve into the potential impact of crude banking characteristic selection on the baseline findings, we introduce two alternative efficiency specifications: broader and narrower measures for financial institutions.

The EFI broad index encompasses the crude banking characteristics employed in the baseline specification (NIM, lending-deposit spread, non-interest income to total income, overhead costs to total assets, and bank's ROA) and augments them with the bank's return on equity (ROE), a country's bank concentration, and five-bank asset concentration. Bank's ROE represents the commercial bank's after-tax net income relative to its yearly averaged equity. A country's bank concentration is measured as the share of assets held by the three largest commercial banks in total commercial banking assets, while five-bank asset concentration reflects the share of assets held by the five largest banks in total commercial banking assets.

The relationship between low bank profitability and a more competitive banking system is not straightforward. Low profitability may compromise the stability of the banking system, rendering banks more susceptible to runs during crises, as proposed by Diamond and Dybvig (1983). To address these concerns, we introduce an EFI narrow index that excludes ROA as an input characteristic in the B-PCA. Specifically, the narrow index utilizes the crude banking characteristics of NIM, lending-deposit spread, non-interest income to total income, and the banks' overhead costs to total assets as inputs in the B-PCA.

Mirroring the EFI index, the narrow index exhibits negative loadings for the banks' NIM, lending-minus-deposits spread, and bank overhead costs. The bank's non-interest income to total income bears a negligible impact on the narrow index. On average, the narrow index accounts for approximately 51 percent of the variation in the crude banking efficiency measures.[16] The broad index similarly exhibits negative loadings for the banks' NIM, lending-minus-deposits spread, overhead costs to total assets, ROA, and ROE. Bank's non-interest income to total income, bank concentration, and five bank asset concentration characteristics do not influence the broad index. On average, the broad index captures approximately 30 percent of the variation in the crude banking efficiency measures.[17]

Employing the narrower and broader indexes, we investigate the baseline model presented in equation (5). Table 3 summarizes the findings. The interaction term between the index and the crisis dummy is positive and statistically significant, regardless of whether we utilize the EFI broad index or the EFI narrow index. Consequently, our results remain largely unaffected by the selection of input variables in the B-PCA.

[Please Insert Table 4 Here]

5.4. Robustness Analysis

To thoroughly assess the resilience of the relationship between EFI and firm investment during crises, we conducted a series of robustness tests. We investigated whether the baseline findings persist when employing: (1) alternative EFI index construction methods, (2) EFI index values from two years prior to the crisis, (3) stock market capitalization controls, and (4) macroeconomic factors controls.

5.4.1. EFI Index Estimation Using Alternative PCA Methods

The sensitivity of the results to the EFI index construction method is an important consideration. To address this concern, we construct EFI indices using both conventional PCA and probabilistic PCA (P-PCA) approaches.

For the conventional PCA, we remove approximately half of the input data, as any missing value for a country-year necessitated the elimination of the entire country-year data point. This resulted in a substantial data loss, but it allowed for a rigorous examination of the robustness of our findings. Consistent with our baseline approach, we utilized the first principal component derived from the conventional PCA as our simplified EFI index. Subsequently, we incorporated this index into the baseline regression model predicting firm investment.

[16] Figures A2 and A3 in the Appendix plot the factor loadings from the B-PCA for the first two principal components using the broader and narrower definitions, respectively.

[17] Figure A4 in the Appendix plots the total variation in crude banking characteristics that is captured by the first principal component, which is the EFI index. In addition to the EFI index, we report the total variation captured by the EFI broad index and the narrow index, which are introduced in Section 5.3.

Similarly, we constructed an EFI index using P-PCA, employing an EM algorithm for probabilistic principal component analysis (Roweis 1997; Tipping & Bishop 1999).

Table 5, Panels A and B, present the results obtained using the simplified EFI index and the P-PCA-based EFI index. In both cases, the association between EFI and investment during the crisis remains positive and statistically significant. These findings suggest that our results are robust to the methodology used to compute the EFI index.

For completion, we examine the baseline regression in (5) using the IMF's financial institutions efficiency index. Our findings indicate that the IMF's index does not exhibit a statistically significant predictive power on investment levels within our sample period. This result is presented in Table A2 of the Appendix. This suggests that the IMF's index may be capturing factors beyond the scope of financial institutions efficiency that influence firm investment decisions.

5.4.2. Two-years Prior EFI Index

A potential concern arises from the possibility that banking efficiency in the year preceding the COVID-19 crisis may be influenced by country-specific variations in crisis anticipation. Consequently, the predetermined nature of banking efficiency one year's prior may be compromised, potentially confounding the interpretation of our findings. To address this concern, we adopt the approach proposed by Duchin *et al.* (2010) and re-estimate the baseline specification utilizing banking efficiency indexes from further back in time.

Panel C presents the results using EFI index from two years prior to the crisis. The coefficient associated with the interaction term between EFI index and crisis indicator remains positive and statistically significant. Similar results (not reported) are obtained when employing banking efficiency indexes from three years prior to the crisis.

5.4.3. Controlling for Stock Market Capitalization

During economic crises, firms may turn to equity financing for their investment needs. To disentangle the effects of banking credit from that of a firm's ability to issue equity at a low cost, we re-run the baseline model controlling for each country's stock market capitalization. Stock market capitalization is calculated as the total value of all traded shares in a stock market exchange as a percentage of GDP.

In Panel D, we estimate the baseline model controlling for stock market capitalization. The significant impact of EFI on firm investment, even after controlling for the effects of the stock market, persists.

5.4.4. Accounting for Macroeconomic Influences

To comprehensively assess the impact of our independent variables on firm investment decisions, we incorporate a panel of macroeconomic variables that are well-documented to influence firm-level investment behavior. These macroeconomic factors, encompassing contemporaneous GDP growth, interest rate, and inflation rate are introduced to capture the broader economic environment in which firms operate and make investment decisions.

Panel E presents the findings after controlling for these macroeconomic variables. Notably, the qualitative nature of the results remains consistent, even after accounting for these external economic influences. This robustness underscores the significance of EFI in driving firm investment decisions, even amidst the fluctuations of the broader macroeconomic landscape.

[Please Insert Table 5 Here]

5.4.5. Controlling for Monetary Effects and Bank Capital Regulations

The influence of banking efficiency may be intertwined with central bank policies implemented during the pandemic. Central banks worldwide employed various monetary tools in response to the pandemic. To isolate the impact of monetary policy and exchange rates, we examine the effect of banking efficiency on firm investment within the Eurozone. Monetary and conventional credit instruments in the Eurozone fall under the purview of the European Central Bank, and pre-crisis interest rates were at low levels (Benmelech & Tzur-Ilan 2020). For the sample of Eurozone, we continue to observe that firms in economies with efficient banking institutions exhibit lower investment sensitivity to crises.

We also investigate whether the effect of banking efficiency is present in both developed and emerging markets. We apply the baseline model to both developed and emerging market samples. Our findings indicate that banking efficiency plays a crucial role in firm investment behavior during economic crises, regardless of market development status.

Furthermore, we explore whether the effect of banking efficiency on investment is contingent upon the severity of bank capital regulations. The stringency of bank capital regulations encompasses both minimum capital requirements and the rigidity of regulations governing the nature and origin of regulatory capital. Overall capital stringency level assesses whether capital requirements adequately reflect specific risk elements – credit risk, market risk, and operational risk – and deducts certain market value losses from capital before determining minimum capital adequacy. We calculate overall capital stringency level using the World Bank's 2019 Bank Regulation and Supervision Survey, employing the methodology proposed by Barth *et al.* (2013). We categorize markets with an overall capital stringency score of 7 as high capital stringency markets, with the remainder classified as low capital stringency markets. We observe that the impact of banking efficiency during economic crises is evident in countries with both high and low stringency of bank capital regulations. For conciseness, we present all robustness tables in Tables A3 and A4 in the Appendix.

6. Banking Efficiency and the Cross-section of Firms

We now delve into the intricate mechanisms through which banking efficiency impacts its influence on firm investment. Specifically, we scrutinize our second hypothesis, which posits that the effect of banking efficiency on investment during an economic crisis is amplified for firms with a greater reliance on external financing. Additionally, we investigate our third hypothesis, which asserts that the impact of banking efficiency on investment is more pronounced for firms endowed with a larger pool of collateral assets.

6.1. Banking Efficiency and Investment: External Financing

The first channel hinges upon an industry's degree of dependence on external finance. Following Rajan and Zingales (1998), we quantify external finance dependence by aggregating a firm's capital expenditure minus its cash flow over the decade (2010-2019 in our study), and subsequently scaling this value by the sum of capital expenditure. We then compute the median value for three-digit SIC industries based on U.S. data. To distinguish between industries with high and low levels of external finance dependence, we construct a dummy variable, *High External Fin Dependent*, that assumes the value of one if an industry's external finance dependence is above the median, and zero otherwise.

The effects of banking efficiency on firm investment during the pandemic should be more pronounced in industries characterized by high levels of external financing. In essence, firms that heavily depend on external financing sources are less likely to curtail their investment activities if they can secure the necessary credit during the crisis at a favorable intermediary cost. To capture this effect, we introduce a double interaction term that includes the EFI index, the crisis dummy, and the industry dummy variable.

We then estimate the model:

$$\begin{aligned} Inv_{i,c,t} &= \alpha_i + \tau_t \\ &\quad + \beta_1\, EFI_{c,t-1} + \beta_2\, EFI_{c,t-1} \cdot crisis + \beta_3\, EFI_{c,t-1} \cdot crisis \cdot ExtFin \\ &\quad + \beta_5\, crisis \cdot ExtFin + \beta_6\, \mathrm{X}_{i,t-1} + \varepsilon_{i,t}\,, \qquad \cdots (6) \end{aligned}$$

where the coefficient on the double interaction term β_3 is the variable of interest. We anticipate that β_3 will be positive, reflecting the higher magnitude of EFI's mitigating effect on investment contraction during a crisis for firms with a greater reliance on external financing.

The findings of estimating equation (6) are presented in Table 6. The coefficient on the double interaction term exhibits a positive sign and is statistically significant at the conventional 5% level for both total and capital investment. These results align with hypothesis 2, which posits that banking efficiency's impact on investment is more pronounced during an economic crisis for firms with a greater dependence on external financing.

[Please Insert Table 6 Here]

6.1.1. Survey Data on Bank Financing

To further investigate our findings, we delve into the relationship between banking efficiency and capital investment by examining whether the effect is more pronounced for countries with a higher proportion of firms relying on bank loans to finance investment. We employ data from the World Bank Enterprise Surveys, encompassing 26 countries during our sample period.

For each year, we classify countries into two categories: *High Bank Financing* countries, characterized by a number of firms using banks to finance investment above the median, and *Low Bank Financing* countries, characterized by a number of firms using banks to finance investment below the median. Argentina, Belgium, Bulgaria, Colombia, France, Italy, Jordan, Morocco, Malaysia, Peru, Poland, and Spain fall into the high bank financing category, while Austria, Croatia, Cyprus, Denmark, Egypt, Finland, Greece, Netherlands, Romania, Russia, Sweden, Thailand, Turkey, and South Africa fall into the low bank financing category.

Table 7, columns (1) and (2), presents the results for countries with a high proportion of firms using banks to finance investment. In this sample, banking efficiency exerts a significant and positive influence on firm-level investment during the crisis. Conversely, as shown in columns (3) and (4), banking efficiency has no discernible impact on investment for firms in countries with a low proportion of firms using banks to finance investments. These findings corroborate the hypothesis that the impact of banking efficiency on investment is more pronounced in firms that utilize banks to finance investment. This analysis highlights the crucial role played by banks in facilitating investment, particularly during periods of economic turbulence.

[Please Insert Table 7 Here]

6.2. Banking Efficiency and Investment: Firm Collateral

To delve into the collateral hypothesis, we examine whether the impact of banking efficiency on investment during the crisis is amplified for firms with assets suitable for pledging as bank loan collateral. To assess this channel, we introduce a double interaction term between the EFI index, a crisis dummy, and a dummy variable identifying firms with high collateral assets.

We employ two proxies for collateral. The first is based on the firm's tangibility ratio of fixed to total investments. Fixed investments 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 of fixed to total investments and subsequently divide the sample along the median. The indicator variable 'High Tangibility' equals one if the firm's tangibility ratio is above the annual median within the country, and zero otherwise.

Our second proxy is based on the cyclicality of durable goods industry sales. Durable goods producers exhibit heightened sensitivity to business cycles compared to nondurable and services producers. A negative demand shock, such as the COVID-19 pandemic, is likely to impact all potential alternative users of a durable producer's assets, consequently reducing tangibility (Almeida & Campello 2007). Employing industry input-output accounts, as per Gomes *et al.* (2009), we classify consumption good producers into durable and non-durable categories.

We estimate the following regression model:

$$
\begin{aligned}
Inv_{i,c,t} = {} & \alpha_i + \tau_t \\
& + \beta_1\, EFI_{c,t-1} + \beta_2\, EFI_{c,t-1} \cdot crisis + \beta_3\, EFI_{c,t-1} \cdot crisis \cdot collateral \\
& + \beta_5\, crisis \cdot collateral + \beta_6\, \mathrm{X}_{i,t-1} + \varepsilon_{i,t}\,, \qquad \cdots (7)
\end{aligned}
$$

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 8 presents the regression results, revealing a positive and statistically significant coefficient for the double interaction term in both total and capital investment equations. This suggests that collateral-rich firms can effectively leverage bank credit as a hedging mechanism against cash flow uncertainties. Consequently, access to efficient banking institutions mitigates the adverse impact of economic crises on firm investment activities. These findings corroborate hypothesis 3, which postulates that the influence of banking efficiency on firm investment is more pronounced during economic downturns, particularly for firms with ample collateral assets.

[Please Insert Table 8 Here]

6.3. Banking Efficiency and Investment: Financially Constrained Firms

Thus far, we have established that efficient financial institutions play a crucial role in mitigating the adverse effects of economic crises on firm investment. This effect is particularly pronounced for firms with collateralizable assets. In this section, we delve into the question of whether this safety net effect extends to firms that are genuinely in need of financing, rather than those that simply have the means to secure it. Specifically, we investigate whether the positive impact of efficient financial institutions on investment during an economic crisis is more pronounced for financing-constrained firms.

We employ two metrics to assess financial constraints at the firm level: the sensitivity of cash flow to investment and the sensitivity of cash flow to cash holdings. These measures are grounded in the literature, which suggests that firms experiencing financial constraints exhibit a heightened sensitivity of cash flow to both investment and cash holdings (Fazzari *et al.* 1988; Almeida & Campello 2007).

To quantify the investment-to-cash flow sensitivity, we employ a regression of investment on cash flow while incorporating lagged control variables, including market value, leverage, and Tobin's *q*, utilizing data from the past decade. In line with the approach adopted by Farre-Mensa and Ljungqvist (2016), we construct a dummy variable (High Inv-CF Sensitivity) to identify firms with severe financial constraints. This variable assumes a value of 1 if the investment-to-cash flow sensitivity falls within the top tercile (by country-year) and 0 otherwise. A similar methodology is employed to create a dummy variable (High Cash-CF Sensitivity) based on cash-to-cash flow sensitivity.

Our findings, presented in Table 9, do not provide support for the hypothesis that efficient banks allocate a larger share of their lending to financially constrained firms during periods of economic downturn. This suggests that the protective effect of efficient financial institutions on firm investment during crises may not extend to firms that are genuinely in need of financing.

[Please Insert Table 9 Here]

7. Exposure to the COVID-19 Shock

Efficient banking institutions serve as a critical safety net for firms during periods of demand slowdown, cushioning the impact of crises and fostering resilience. To further substantiate this hypothesis, we delve into a sub-sample analysis, investigating whether the protective effect of banking efficiency on investment is amplified for firms with greater exposure to the COVID-19 shock. We employ three proxies to capture a firm's exposure to the pandemic's disruption: new COVID-19 cases, the level of economic support provided by the government, and the extent of social distancing measures implemented.

The first proxy, new COVID-19 cases, reflects the cross-country variation in pandemic severity. We categorize countries with new cases exceeding the median as high COVID exposure markets, while those below the median are considered low COVID exposure markets.

The second proxy, the level of economic support provided by the government, captures the heterogeneity in government intervention aimed at bolstering the private sector. To gauge the extent of government support, we utilize the country-level economic support indexes from the Oxford COVID-19 Government Response Tracker (OxCGRT), as detailed by Hale *et al.* (2021). We categorize markets with an index value above the median as high government support markets, and those below the median as low government support markets.

The third proxy delves into the impact of social distancing measures. 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. As a result, this proxy arguably offers the most comprehensive assessment of vulnerability to social distancing measures (Pagano *et al.* 2023). We classify non-resilient industries as those with an affected share above the median and resilient industries as those with an affected share below the median.

Table 10 presents the baseline findings for each subsample. The influence of banking efficiency on capital investment is markedly amplified in markets experiencing a surge in new COVID-19 cases and markets characterized by limited government economic support. The effect is also substantially greater for non-resilient industries. These subsample results underscore the notion that efficient financial institutions serve as a safety net for firms during non-financial economic crises. In countries with extensive government support, the demand for bank credit is significantly lower, as the government can directly provide the necessary financing to firms. Conversely, non-resilient industries exhibit a heightened demand for bank credit due to their greater susceptibility to economic shocks and potential limitations in accessing alternative financing sources.

[Please Insert Table 10 Here]

8. Banking Efficiency and the Supply of Credit

An enduring question in financial economics is whether higher-quality financial institutions play a role in mitigating the adverse impacts of economic crises by supplying a larger quantity of credit. To address this question, we leverage a comprehensive dataset of quarterly country-level credit data from the Bank of International Settlements (BIS) spanning the period from 2018 to 2021, encompassing two years preceding the COVID-19 crisis and two years following its onset. Our analysis focuses on three key credit variables: the supply of bank credit relative to GDP, the total credit borrowed by households relative to GDP, and the total credit borrowed by corporations relative to GDP.

To empirically examine the relationship between banking efficiency and credit supply during the COVID-19 crisis, we employ a panel regression framework with fixed effects for country, year, and quarter. We include real GDP growth as a control variable to account for potential macroeconomic factors that may influence credit supply. Additionally, we construct an interaction term between the lagged EFI index and a crisis dummy variable to capture the impact of banking efficiency on credit supply during the COVID-19 crisis.

Table 11 presents the results of our analysis. Panel A summarizes the descriptive statistics for the credit variables, while Panel B reports the estimated regression coefficients. Notably, the interaction term between the lagged EFI index and the crisis dummy variable exhibits positive and statistically significant coefficients for all three credit variables. This finding provides compelling evidence that countries with more efficient financial institutions were able to provide a greater volume of bank credit to the private non-financial sector during the COVID-19 crisis. [18] This increased credit supply is further reflected in the higher borrowing levels observed among both households and corporations during the crisis period.

Our findings have significant implications for policymakers, underscoring the importance of fostering a sound and efficient banking sector to enhance the resilience of economies in the face of crises. By promoting banking efficiency, policymakers can equip

[18] We find that our results are robust to the inclusion of other control factors such as the business confidence, consumer confidence, and leading indicator for business cycle movements.

financial institutions with the capacity to expand credit provision during times of economic crises, thereby mitigating the adverse effects of crises on private sector investments.

[Please Insert Table 11 Here]

9. Conclusion

In this study, we introduce novel country-level time-varying indices that capture banking efficiency. Due to data limitations, certain crude characteristics of banking institutions in some international markets are either missing or unobserved. Recognizing the limitations of traditional data sources, we employ sophisticated machine learning techniques, specifically a Bayesian treatment of principal component analysis, to estimate banking efficiency indices.

Our findings reveal that the adverse impact of an economic crisis on firm investment is mitigated for those firms that have access to efficient financial institutions. During the COVID-19 crisis, the sensitivity of capital investment to an economic crisis was considerably lower in economies with efficient banking institutions. This mitigating effect is particularly pronounced for firms operating in sectors that are more reliant on external financing sources compared to those that rely primarily on internal cash flow to fund projects.

Furthermore, our study reveals a nuanced interaction between banking efficiency, firm investment, and collateralizability. Firms with higher levels of collateralizable assets are disproportionately benefited from the presence of efficient banks during economic crises. This finding suggests that efficient banks are better equipped to assess and manage credit risk, enabling them to extend loans to firms with valuable assets even during periods of heightened financial stress. However, our analysis does not provide evidence to support the notion that efficient banks specifically target financially constrained firms during crises. This implies that the safety net effect of efficient financial institutions may not extend to all firms in need of financing.

Our study provides novel insights into the role of banking efficiency in mitigating the adverse effects of economic crises on firm investment. The findings highlight the importance of fostering a robust and efficient banking sector to enhance the resilience of the real economy to economic shocks.

References

Acharya, V., Steffen, S., 2020a. Stress tests" for banks as liquidity insurers in a time of COVID.

Acharya, V.V., Steffen, S., 2020b. The risk of being a fallen angel and the corporate dash for cash in the midst of COVID.

Aghion, P., Angeletos, G.-M., Banerjee, A., Manova, K., 2010. Volatility and growth: Credit constraints and the composition of investment. Journal of Monetary Economics 57, 246-265

Aghion, P., Bolton, P., 1997. A theory of trickle-down growth and development. The review of economic studies 64, 151-172

Aizenman, J., Jinjarak, Y., Park, D., 2015. Financial development and output growth in developing Asia and Latin America: A comparative sectoral analysis. National Bureau of Economic Research

Albuquerque, R., Hopenhayn, H.A., 2004. Optimal lending contracts and firm dynamics. The Review of Economic Studies 71, 285-315

Albuquerque, R., Koskinen, Y., Yang, S., Zhang, C., 2020. Resiliency of environmental and social stocks: An analysis of the exogenous COVID-19 market crash. The Review of Corporate Finance Studies 9, 593-621

Allen, L., Rai, A., 1996. Operational efficiency in banking: An international comparison. Journal of Banking & Finance 20, 655-672

Almeida, H., Campello, M., 2007. Financial constraints, asset tangibility, and corporate investment. The Review of Financial Studies 20, 1429-1460

Attias, H., 1999. Inferring parameters and structure of latent variable models by variational bayes. In: Proceedings of the Fifteenth conference on Uncertainty in artificial intelligence, pp. 21-30

Bagehot, W., 1873. Lombard Street, Homewood, IL: Richard D. Irwin,(1962 Edition)

Barth, J.R., Caprio, G., Levine, R., 2013. Bank regulation and supervision in 180 countries from 1999 to 2011. Journal of Financial Economic Policy

Benmelech, E., Tzur-Ilan, N., 2020. The determinants of fiscal and monetary policies during the COVID-19 crisis. National Bureau of Economic Research

Berg, S.A., Førsund, F.R., Hjalmarsson, L., Suominen, M., 1993. Banking efficiency in the Nordic countries. Journal of Banking & Finance 17, 371-388

Berger, A.N., Demirgüç-Kunt, A., 2021. Banking research in the time of COVID-19. Journal of Financial Stability 57, 100939

Berger, A.N., Sedunov, J., 2017. Bank liquidity creation and real economic output. Journal of Banking & Finance 81, 1-19

Berger, P.G., Ofek, E., Swary, I., 1996. Investor valuation of the abandonment option. Journal of financial economics 42, 259-287

Bernanke, B.S., 1983. Non-monetary effects of the financial crisis in the propagation of the Great Depression. National Bureau of Economic Research

Bishop, C., 1998. Bayesian pca. Advances in neural information processing systems 11

Bishop, C.M., 1999. Variational principal components.

Boot, A., Thakor, A., Udell, G., 1991. Secured Lending and Default Risk: Equilibrium Analysis, Policy Implications and Empirical Results. Economic Journal 101, 458-72

Brock, P.L., Suarez, L.R., 2000. Understanding the behavior of bank spreads in Latin America. Journal of development Economics 63, 113-134

Caballero, R.J., Krishnamurthy, A., 2001. International and domestic collateral constraints in a model of emerging market crises. Journal of Monetary Economics 48, 513-548

Campello, M., Graham, J.R., Harvey, C.R., 2010. The real effects of financial constraints: Evidence from a financial crisis. Journal of Financial Economics 97, 470-487

Cetorelli, N., Gambera, M., 2001. Banking market structure, financial dependence and growth: International evidence from industry data. The Journal of Finance 56, 617-648

Chaney, T., Sraer, D., Thesmar, D., 2012. The collateral channel: How real estate shocks affect corporate investment. American Economic Review 102, 2381-2409

Chodorow-Reich, G., 2013. The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008–9 Financial Crisis *. The Quarterly Journal of Economics 129, 1-59

Cihak, M., Demirgüç-Kunt, A., Feyen, E., Levine, R., 2012. Benchmarking financial systems around the world. The World Bank.

Cooley, T., Marimon, R., Quadrini, V., 2004. Aggregate Consequences of Limited Contract Enforceability. Journal of Political Economy 112, 817-847

Dell'Ariccia, G., Detragiache, E., Rajan, R., 2008. The real effect of banking crises. Journal of Financial Intermediation 17, 89-112

Diamond, D.W., Dybvig, P.H., 1983. Bank runs, deposit insurance, and liquidity. Journal of political economy 91, 401-419

Ding, W., Levine, R., Lin, C., Xie, W., 2021. Corporate immunity to the COVID-19 pandemic. Journal of Financial Economics 141, 802-830

Duchin, R., Ozbas, O., Sensoy, B.A., 2010. Costly external finance, corporate investment, and the subprime mortgage credit crisis. Journal of financial economics 97, 418-435

Ellul, A., Erel, I., Rajan, U., 2020. The COVID-19 Pandemic Crisis and Corporate Finance. The Review of Corporate Finance Studies 9, 421

Erel, I., Jang, Y., Weisbach, M.S., 2015. Do acquisitions relieve target firms' financial constraints? The Journal of Finance 70, 289-328

Fahlenbrach, R., Rageth, K., Stulz, R.M., 2021. How valuable is financial flexibility when revenue stops? Evidence from the COVID-19 crisis. The Review of Financial Studies 34, 5474-5521

Farre-Mensa, J., Ljungqvist, A., 2016. Do Measures of Financial Constraints Measure Financial Constraints? The Review of Financial Studies, 271-308

Fazzari, S.M., Hubbard, R.G., Petersen, B.C., Blinder, A.S., Poterba, J.M., 1988. Financing Constraints and Corporate Investment. Brookings Papers on Economic Activity 1988, 141-206

Fecher, F., Pestieau, P., 1993. Efficiency and competition in OECD financial services. The measurement of productive efficiency: Techniques and applications, 374-385

Gan, J., 2007. Collateral, debt capacity, and corporate investment: Evidence from a natural experiment. Journal of Financial Economics 85, 709-734

Giroud, X., Mueller, H.M., 2017. Firm leverage, consumer demand, and employment losses during the great recession. The Quarterly Journal of Economics 132, 271-316

Gomes, J.F., Kogan, L., Yogo, M., 2009. Durability of output and expected stock returns. Journal of Political Economy 117, 941-986

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., Tatlow, H., 2021. A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). Nature Human Behaviour

Hart, O., Moore, J., 1994. A theory of debt based on the inalienability of human capital. The Quarterly Journal of Economics 109, 841-879

Holmstrom, B., Tirole, J., 1997. Financial Intermediation, Loanable Funds, and the Real Sector. The Quarterly Journal of Economics, 663-691

Inderst, R., Mueller, H.M., 2007. A lender-based theory of collateral. Journal of Financial Economics 84, 826-859

Jayaratne, J., Strahan, P.E., 1996. The finance-growth nexus: Evidence from bank branch deregulation. The Quarterly Journal of Economics 111, 639-670

Kahle, K.M., Stulz, R.M., 2013. Access to capital, investment, and the financial crisis. Journal of Financial Economics 110, 280-299

King, R.G., Levine, R., 1993. Finance and growth: Schumpeter might be right. The Quarterly Journal of Economics 108, 717-737

Kiyotaki, N., Moore, J., 1997. Credit cycles. Journal of political economy 105, 211-248

Koren, M., Pető, R., 2020. Business disruptions from social distancing. Plos one 15, e0239113

Krishnan, K., Nandy, D.K., Puri, M., 2014. Does Financing Spur Small Business Productivity? Evidence from a Natural Experiment. The Review of Financial Studies 28, 1768-1809

Kroszner, R.S., Laeven, L., Klingebiel, D., 2007. Banking crises, financial dependence, and growth. Journal of Financial Economics 84, 187-228

Kroszner, R.S., Strahan, P.E., 2014. Regulation and deregulation of the US banking industry: causes, consequences, and implications for the future. In: Economic regulation and its reform: what have we learned? University of Chicago Press, pp. 485-543.

Kwan, S.H., 2003. Operating performance of banks among Asian economies: An international and time series comparison. Journal of Banking & Finance 27, 471-489

Levine, R., 1998. The legal environment, banks, and long-run economic growth. Journal of Money, Credit and Banking, 596-613

Levine, R., 1999. Law, finance, and economic growth. Journal of Financial Intermediation 8, 8-35

Levine, R., Lin, C., Xie, W., 2016. Spare tire? Stock markets, banking crises, and economic recoveries. Journal of Financial Economics 120, 81-101

Levine, R., Zervos, S., 1998. Stock markets, banks, and economic growth. American Economic Review, 537-558

Levine, R., Zervos, S.J., 1993. What we have learned about policy and growth from cross-country regressions? The American Economic Review 83, 426-430

Li, L., Strahan, P.E., Zhang, S., 2020. Banks as lenders of first resort: Evidence from the COVID-19 crisis. The Review of Corporate Finance Studies 9, 472-500

Maudos, J., Solís, L., 2009. The determinants of net interest income in the Mexican banking system: An integrated model. Journal of Banking & Finance 33, 1920-1931

Maudos, J.n., De Guevara, J.F., 2004. Factors explaining the interest margin in the banking sectors of the European Union. Journal of Banking & Finance 28, 2259-2281

Maudos, J.n., Pastor, J.M., Pérez, F., Quesada, J., 2002. Cost and profit efficiency in European banks. Journal of International Financial Markets, Institutions and Money 12, 33-58

Minka, T., 2000. Automatic choice of dimensionality for PCA. Advances in neural information processing systems 13

O'Hara, M., Zhou, X., 2021. Anatomy of a liquidity crisis: Corporate bonds in the COVID-19 crisis. Journal of Financial Economics 142, 46-68

Oba, S., Sato, M.-a., Takemasa, I., Monden, M., Matsubara, K.-i., Ishii, S., 2003. A Bayesian missing value estimation method for gene expression profile data. Bioinformatics 19, 2088-2096

Pagano, M., Wagner, C., Zechner, J., 2023. Disaster resilience and asset prices. Journal of Financial Economics Forthcoming

Papanikolaou, D., Schmidt, L.D., 2022. Working remotely and the supply-side impact of Covid-19. The Review of Asset Pricing Studies 12, 53-111

Pastor, J., Perez, F., Quesada, J., 1997. Efficiency analysis in banking firms: An international comparison. European Journal of Operational Research 98, 395-407

Rajan, R., Zingales, L., 1998. Financial Dependence and Growth. American Economic Review 88, 559-86

Rajan, R.G., 1994. Why bank credit policies fluctuate: A theory and some evidence. The Quarterly Journal of Economics 109, 399-441

Ramelli, S., Wagner, A.F., 2020. Feverish stock price reactions to covid-19.

Roweis, S., 1997. EM algorithms for PCA and SPCA. Advances in neural information processing systems 10

Sahay, M.R., Cihak, M., N'Diaye, M.P., Barajas, M.A., Pena, M.D.A., Bi, R., Gao, Y., Kyobe, A., Nguyen, L., Saborowski, C., 2015. Rethinking Financial Deepening: Stability and Growth in Emerging Markets. International Monetary Fund.

Sato, M.-A., 2001. Online model selection based on the variational Bayes. Neural computation 13, 1649-1681

Saunders, A., Schumacher, L., 2000. The determinants of bank interest rate margins: an international study. Journal of international Money and Finance 19, 813-832

Shleifer, A., Vishny, R.W., 1992. Liquidation values and debt capacity: A market equilibrium approach. The journal of finance 47, 1343-1366

Stiglitz, J.E., Weiss, A., 1981. Credit rationing in markets with imperfect information. The American economic review 71, 393-410

Svirydzenka, K., 2016. Introducing a New Broad-based Index of Financial Development.

Tipping, M.E., Bishop, C.M., 1999. Probabilistic principal component analysis. Journal of the Royal Statistical Society: Series B (Statistical Methodology) 61, 611-622

Wong, K.P., 1997. On the determinants of bank interest margins under credit and interest rate risks. Journal of Banking & Finance 21, 251-271

Figure 1. 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 original crude efficiency 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 original efficiency characteristics.

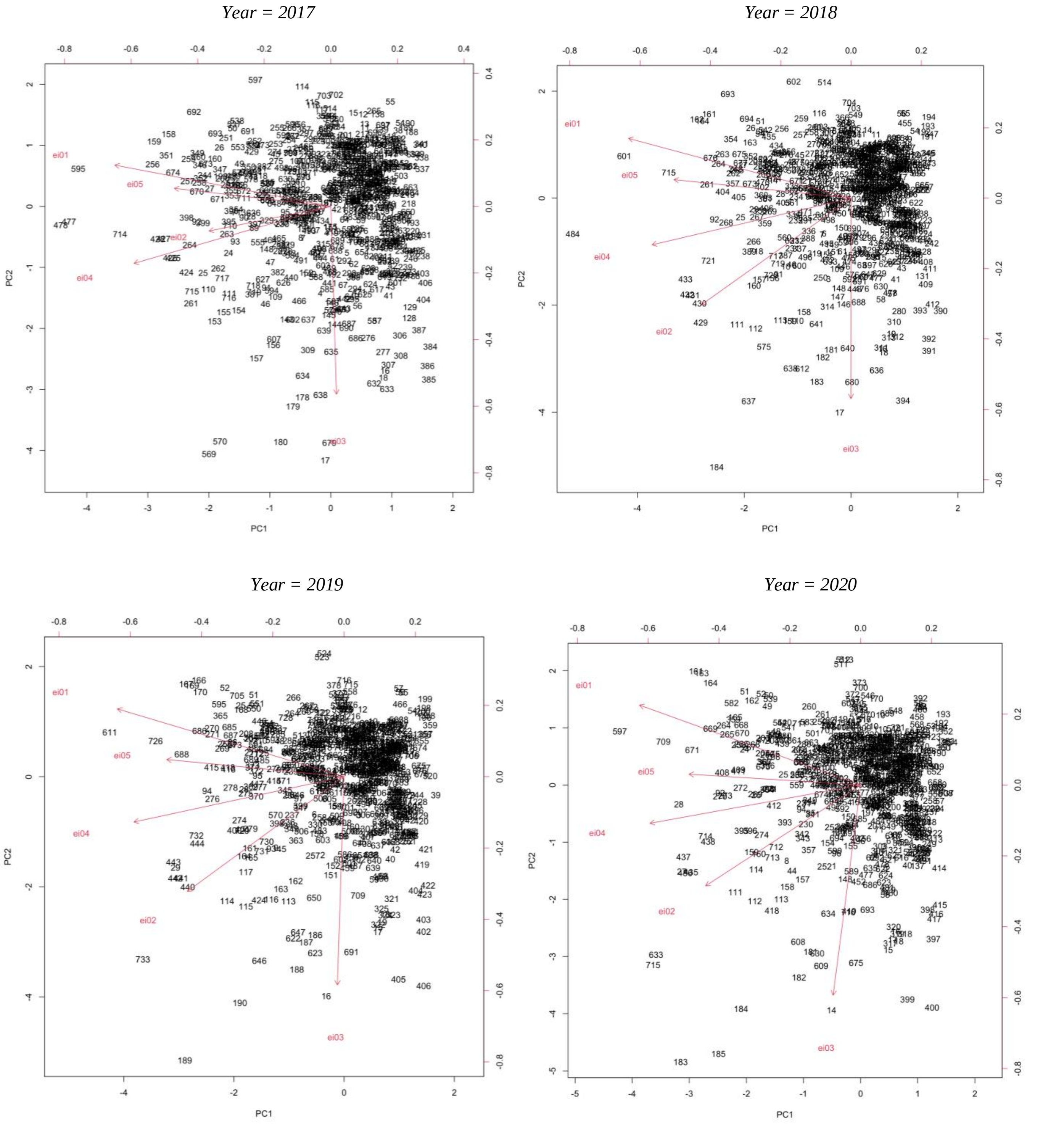
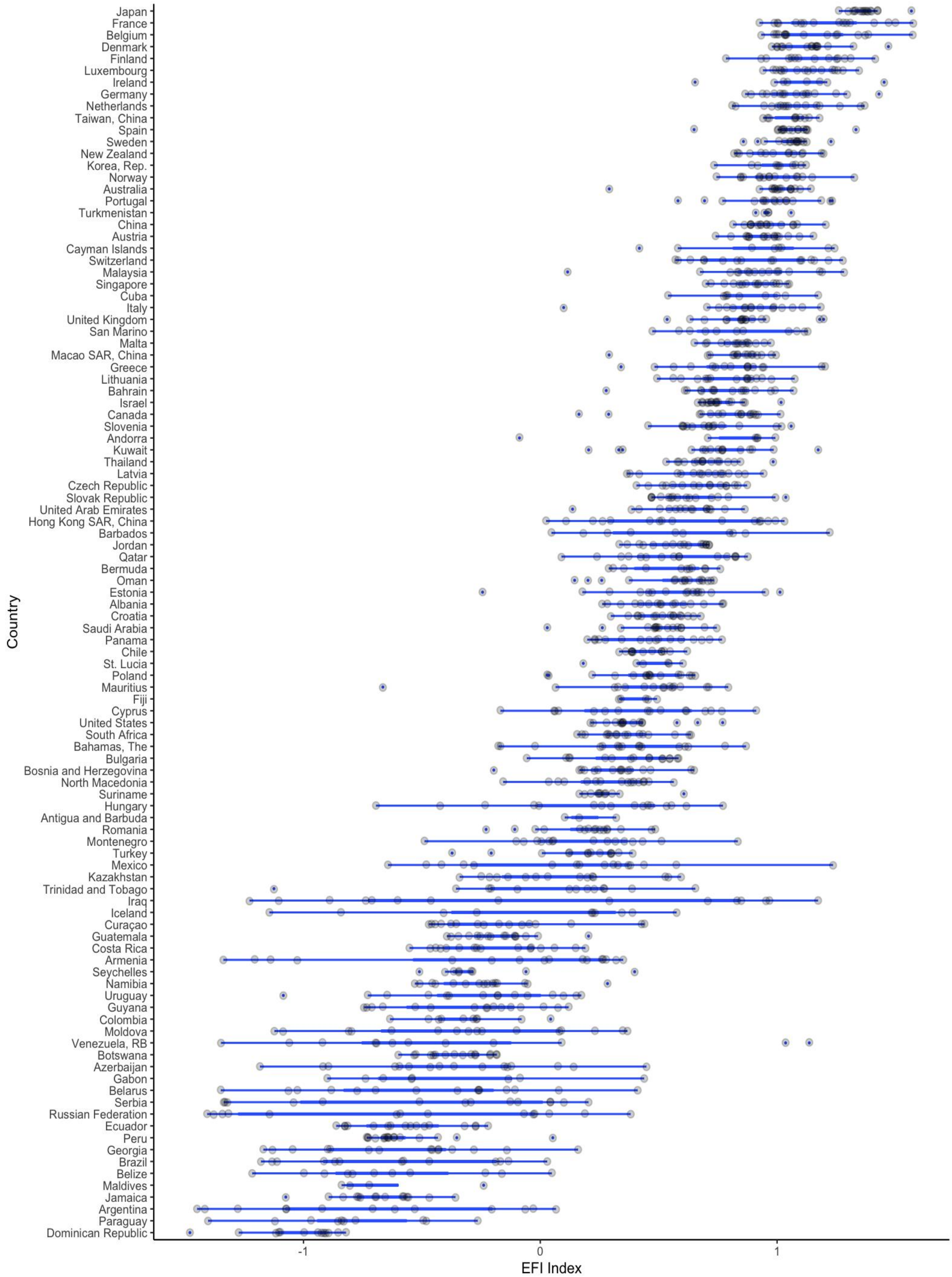


Figure 2. Efficient Financial Institutions (EFI) Index by Market

Note: This figure illustrates the EFI index for each country-year. The EFI 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 EFI index distribution. Panel A depicts high-income economies, while Panel B focuses on low-income economies.

Panel A. Higher Income Economies



Panel B. Lower-Income Markets

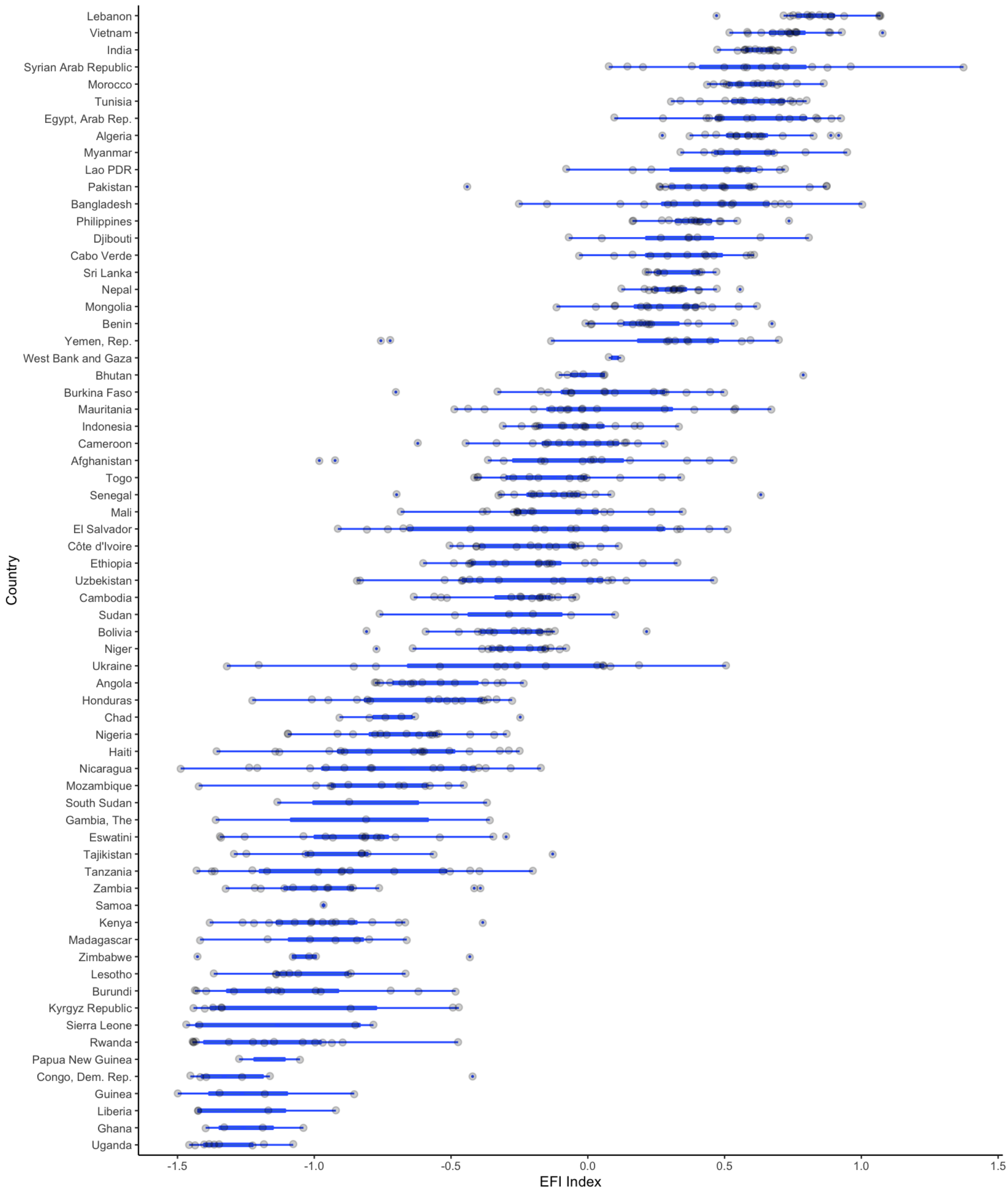
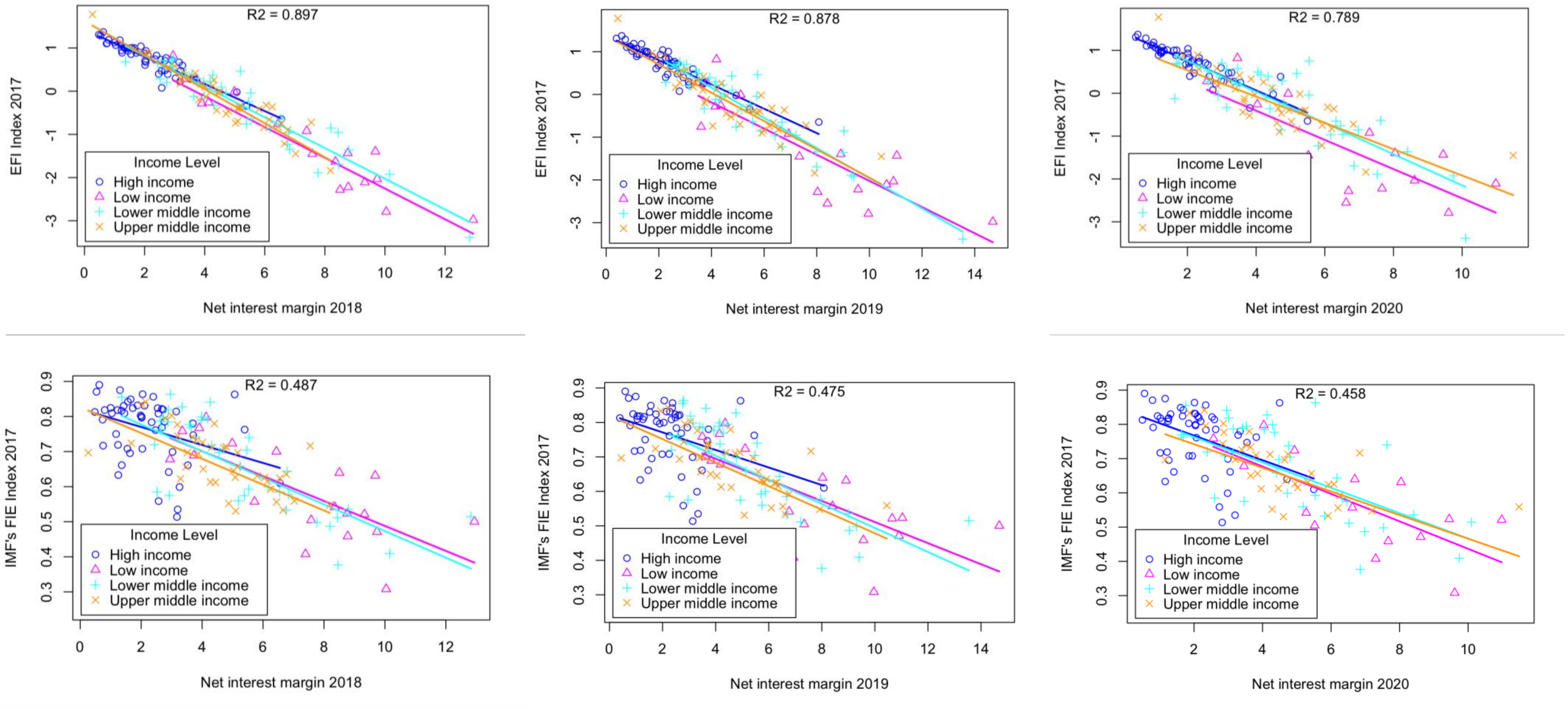


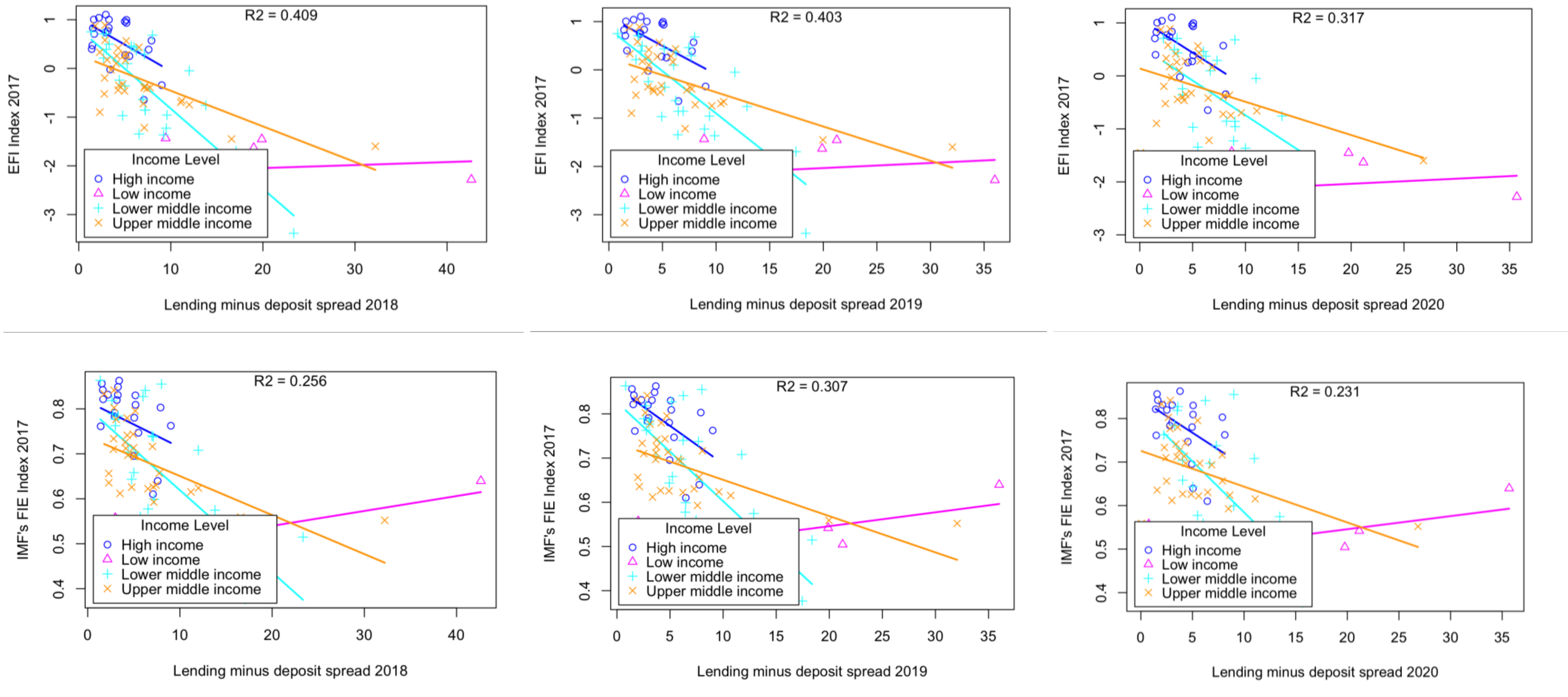
Figure 3: Out-of-Sample Performance: EFI Index versus IMF's FIE Index

Note: This figure compares the out-of-sample performance of the 2017 EFI 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.

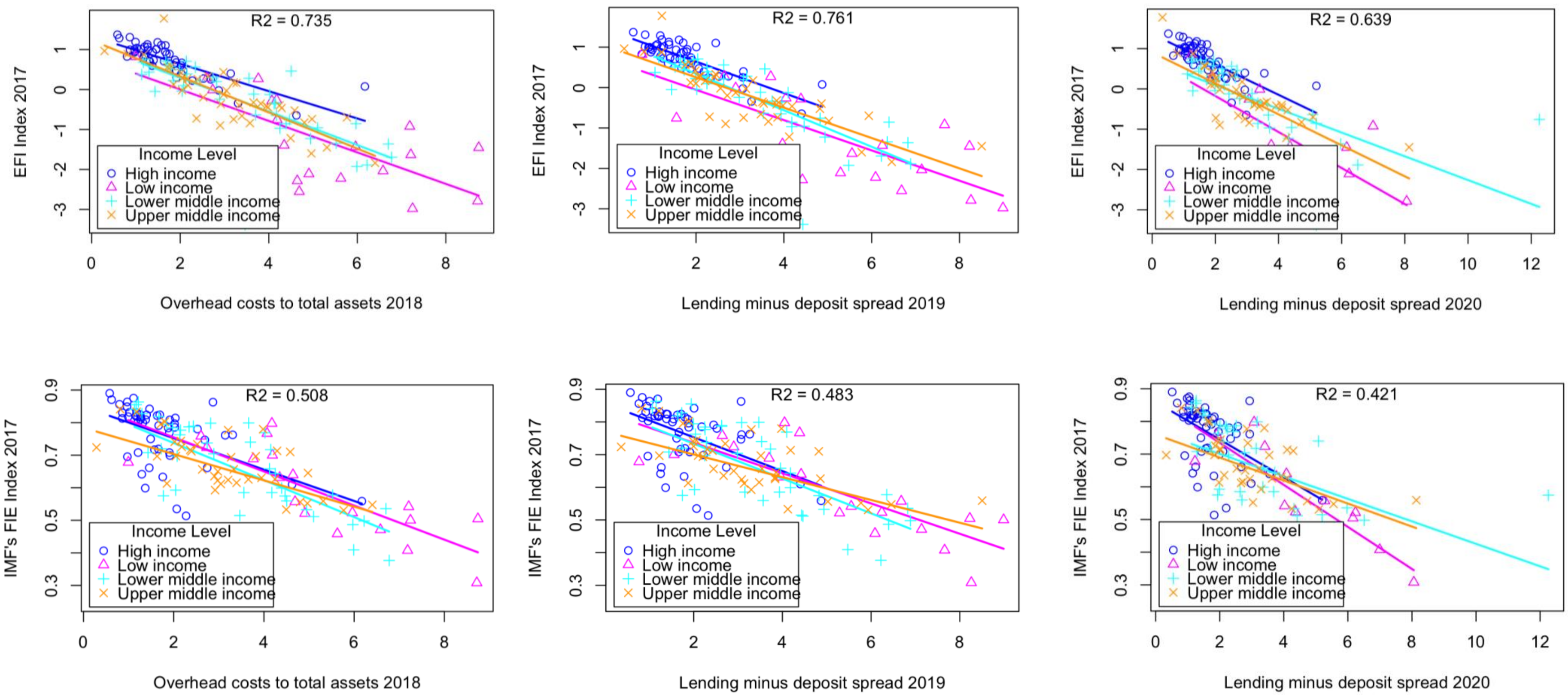
Panel A. Net Interest Margin



Panel B. Lending – Deposit Spread



Panel C. Overhead costs to total assets



Panel D. Bank Profitability (ROA)

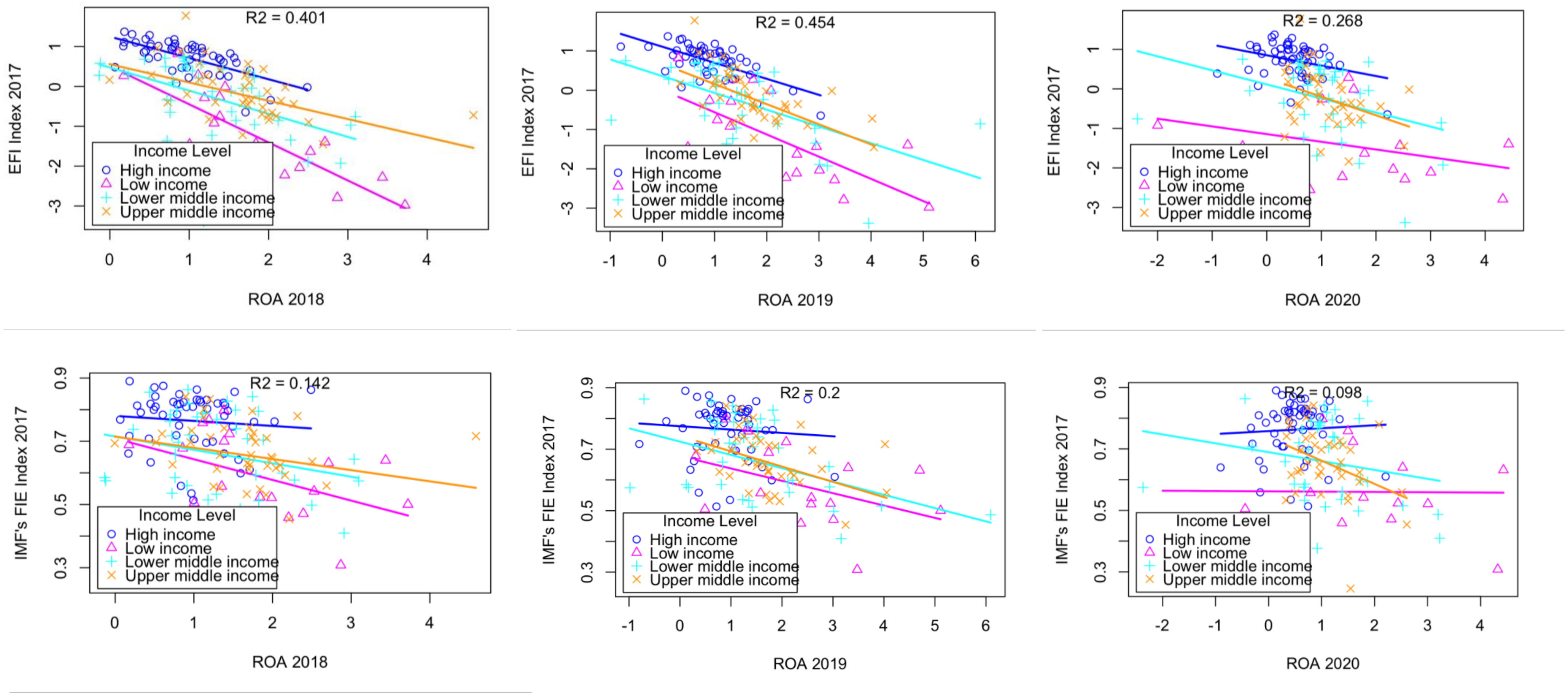


Figure 4. Firm Investment Before and After Shock

Note: This figure illustrates the average firm capital investment for countries with varying levels of banking efficiency. Countries with an EFI index below the median in 2018 are classified as *Low EFI*, while those with an EFI index above the median are classified as *High EFI*. The first stage involves estimating a regression of capital investments on firm-level cash flow to assets, log of market capitalization, Tobin's *q*, leverage, and country-level real GDP growth, incorporating firm and year fixed effects. Subsequently, the estimated residuals for High EFI and Low EFI countries are plotted in the second stage. The figure depicts both the average and the 99 percent confidence intervals. The blue dotted line represents the Covid-19 demand shock.

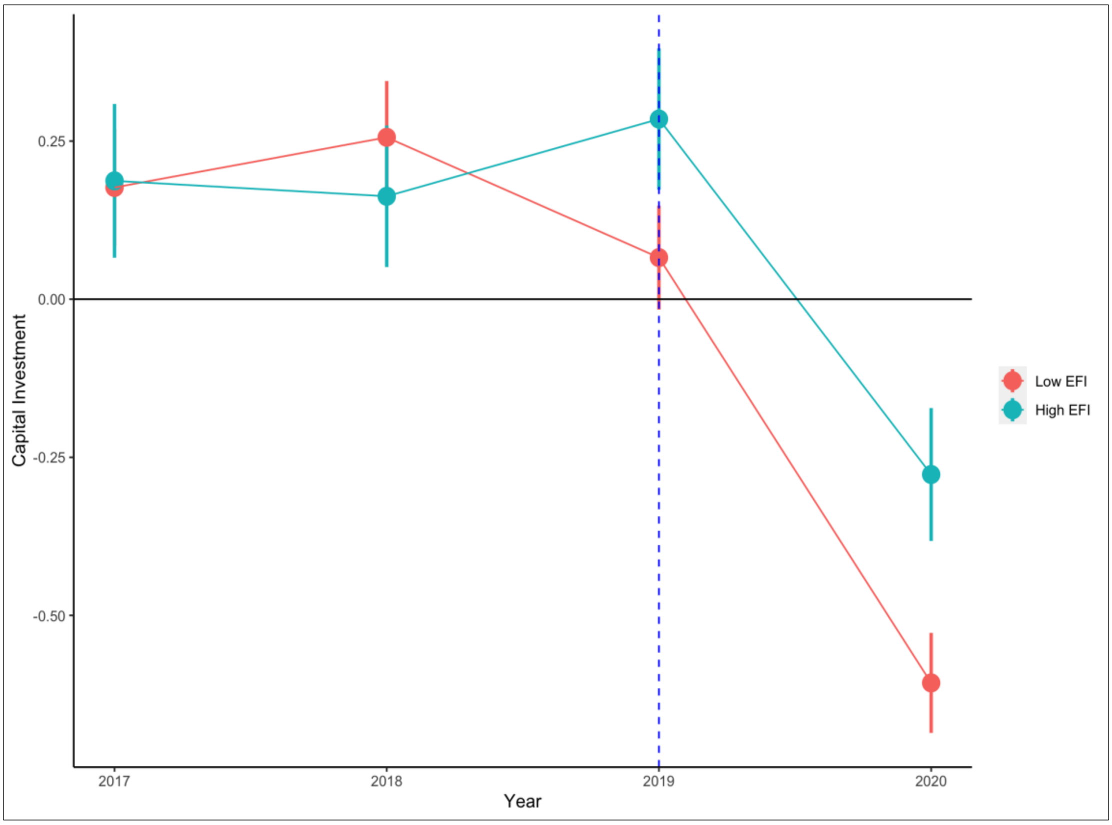


Table 1. Summary Statistics

Note: This table reports the mean statistics of key variables for a sample of Compustat Global yearly observations between 2018 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 EFI Index serves as a measure of overall efficiency in financial institutions. Investment is defined as the ratio of annual total investment (comprising the sum of capital expenditure and R&D expenditure) to the book value of total assets at the beginning of the fiscal year. Capital Investment represents the ratio of annual capital expenditure to the book value of total assets at the beginning of the fiscal year. R&D expenditure reflects the ratio of annual R&D 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.

	2018-2019 Pre-COVID Shock				2020-2021 Post-COVID Shock			
Country	N	EFI Index	Total Investment	Capital Investment	N	EFI Index	Total Investment	Capital Investment
Argentina	71	-1.357	0.170	0.169	70	-2.337	0.075	0.075
Australia	1435	0.995	0.111	0.082	1398	1.003	0.098	0.066
Austria	71	0.977	0.084	0.056	68	1.071	0.074	0.049
Bangladesh	333	0.695	0.067	0.066	336	0.860	0.046	0.045
Belgium	120	0.992	0.070	0.046	106	1.073	0.055	0.035
Brazil	267	-1.350	0.040	0.035	268	-1.004	0.041	0.037
Bulgaria	92	0.329	0.040	0.040	84	0.547	0.024	0.024
Canada	177	0.867	0.112	0.068	171	0.877	0.104	0.064
Chile	139	0.513	0.045	0.045	148	0.450	0.040	0.040
China	7164	0.904	0.075	0.052	7639	0.851	0.075	0.051
Colombia	57	-0.445	0.043	0.043	29	-0.429	0.035	0.035
Croatia	99	0.398	0.058	0.058	98	0.483	0.046	0.044
Cyprus	73	-0.048	0.052	0.052	63	0.161	0.038	0.037
Denmark	138	1.137	0.076	0.041	139	1.180	0.069	0.035
Egypt	207	0.458	0.044	0.044	209	0.182	0.034	0.034
Finland	213	1.352	0.081	0.041	222	1.280	0.074	0.038
France	778	1.360	0.077	0.041	721	1.539	0.068	0.038
Germany	676	1.135	0.080	0.044	632	1.153	0.069	0.035
Greece	213	0.523	0.041	0.033	204	0.718	0.043	0.034
Hong Kong	1955	0.943	0.038	0.031	2022	0.980	0.035	0.027
India	4784	0.563	0.053	0.049	4701	0.526	0.047	0.043

Indonesia	592	-0.215	0.055	0.054	688	-0.073	0.035	0.035
Israel	372	0.746	0.059	0.037	380	0.782	0.047	0.031
Italy	373	0.940	0.051	0.037	407	1.099	0.044	0.031
Japan	5254	1.315	0.048	0.036	5347	1.350	0.042	0.030
Jordan	159	0.375	0.039	0.038	117	0.458	0.028	0.028
Korea	2849	1.008	0.069	0.045	2967	0.864	0.063	0.040
Kuwait	144	0.743	0.034	0.034	71	0.752	0.028	0.028
Malaysia	1516	0.879	0.036	0.034	1562	0.921	0.034	0.032
Mauritius	58	0.543	0.033	0.033	63	0.669	0.031	0.031
Mexico	112	-0.372	0.051	0.051	110	-0.385	0.035	0.035
Netherlands	106	1.021	0.059	0.041	95	1.173	0.048	0.027
New Zealand	173	0.881	0.094	0.048	180	0.829	0.070	0.034
Nigeria	147	-0.758	0.061	0.061	70	-0.553	0.061	0.061
Norway	218	0.980	0.103	0.071	225	0.847	0.075	0.048
Oman	120	0.689	0.037	0.037	119	0.709	0.030	0.029
Pakistan	562	0.544	0.083	0.082	558	0.357	0.052	0.051
Peru	123	-0.626	0.047	0.046	120	-0.315	0.036	0.035
Philippines	262	0.385	0.049	0.048	269	0.218	0.030	0.029
Poland	903	0.452	0.064	0.057	873	0.547	0.060	0.050
Romania	103	0.219	0.053	0.052	96	0.250	0.037	0.036
Russia	230	0.005	0.068	0.068	165	0.045	0.065	0.064
Saudi Arabia	236	0.548	0.039	0.039	251	0.521	0.034	0.033
Singapore	821	0.990	0.035	0.032	825	1.000	0.027	0.024
South Africa	267	0.251	0.055	0.052	239	0.455	0.037	0.035
Spain	175	1.098	0.073	0.052	156	1.214	0.058	0.041
Sri Lanka	367	0.245	0.049	0.049	183	0.220	0.033	0.033
Sweden	973	1.081	0.078	0.029	1002	1.105	0.066	0.021
Switzerland	233	1.162	0.077	0.043	231	1.217	0.070	0.036
Thailand	1062	0.582	0.046	0.046	1123	0.608	0.038	0.037
Turkey	399	0.166	0.070	0.064	435	0.227	0.084	0.075
United Arab Emirates	86	0.681	0.033	0.033	40	0.703	0.027	0.027
The U.K.	1338	0.906	0.072	0.040	1271	0.809	0.059	0.028
The U.S.	4656	0.245	0.106	0.047	4567	0.320	0.093	0.037
Vietnam	550	0.669	0.054	0.054	568	0.553	0.038	0.038

Table 2. Accuracy of the EFI Index: Simulation Results

Note: This simulation intends to analyze the accuracy of the efficiency in financial institutions (EFI) index based on the Bayesian treatment of the 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 EFI index based on the Bayesian PCA. We report the mean and the 95 percent confidence level for correlation between the EFI index and the 1st principal component using a standard PCA.

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)

Table 3. Efficient Financial Institutions and Corporate Investment

Note: This table presents regression estimates of firm investment on country-level EFI indices, utilizing a sample of Compustat Global firms from 2018 to 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 EFI Index is constructed using a Bayesian principal component analysis (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. Total Investment indicates the ratio of annual total investment (sum of capital expenditure and R&D expenditure) to the book value of total assets at the beginning of the fiscal year. 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. 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 firm 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)
Dependent Var =	Total Investment		Capital Investment	
EFI Index $_{t-1}$	0.005**	0.003	0.006***	0.004*
	(2.140)	(1.110)	(2.765)	(1.841)
EFI Index $_{t-1}$ × *Crisis*		0.005***		0.004***
		(4.868)		(4.943)
GDP Growth $_{t-1}$	0.009*	0.007	0.014***	0.012***
	(1.950)	(1.520)	(3.334)	(2.930)
CF/TA $_t$	0.026***	0.026***	0.047***	0.047***
	(4.172)	(4.162)	(10.041)	(10.040)
Ln Mkt Cap $_{t-1}$	-0.007***	-0.007***	-0.001	-0.001
	(-7.187)	(-6.960)	(-1.423)	(-1.168)
Tobin's q_{t-1}	0.008***	0.008***	0.005***	0.004***
	(10.767)	(10.709)	(8.636)	(8.557)
Leverage $_{t-1}$	-0.099***	-0.098***	-0.086***	-0.085***
	(-20.043)	(-20.017)	(-20.792)	(-20.754)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	89,302	89,302	89,302	89,302
Adjusted R^2	0.640	0.641	0.515	0.515

Table 4. Narrower and Broader Measures of EFI Index

Note: This table presents regression estimates of firm investment on country-level EFI indices based on a sample of Compustat Global firms from 2018 to 2021. The sample encompasses publicly listed firms from 55 countries. The EFI Index represents the efficiency of financial institutions. The EFI Broad Index is the first 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, bank concentration, and five bank asset concentration measures. The EFI Narrow Index is the first principal component of the Bayesian treatment of PCA, utilizing net interest margin, lending minus deposits spread, non-interest income to total income, and overhead costs to total assets. 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 U.S. dollars, and all financial variables are winsorized at the 1st and 99th percentiles by country. Firm and year-fixed effects are included in all regressions. *T*-statistics in parentheses are derived from standard errors adjusted for firm 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: Broader Measure of EFI Index

	(1)	(2)	(3)	(4)
Dependent Var =	Total Investment		Capital Investment	
EFI Broad $_{t-1}$	-0.000	-0.002	0.000	-0.002
	(-0.297)	(-1.582)	(0.127)	(-1.508)
EFI Broad $_{t-1}$ × *Crisis*		0.003***		0.003***
		(2.968)		(3.752)
Control Variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	89,302	89,302	89,302	89,302
Adjusted R^2	0.640	0.640	0.514	0.515

Panel B: Narrower Measure of EFI Index

	(1)	(2)	(3)	(4)
Dependent Var =	Total Investment		Capital Investment	
EFI Narrow $_{t-1}$	0.007**	0.002	0.007***	0.004
	(2.324)	(0.839)	(2.769)	(1.456)
EFI Narrow $_{t-1}$× *Crisis*		0.005***		0.004***
		(5.073)		(5.049)
Control Variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	89,302	89,302	89,302	89,302
Adjusted R^2	0.640	0.641	0.515	0.515

Table 5. Efficient Financial Institutions and Investment: Robustness Analysis

Note: This table presents regression estimates of firm investment on country-level EFI indices, employing a sample of Compustat Global firms from 2018 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 EFI 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:* EFI 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 EFI index measured in year *t-2* are presented.

- *Panel D* controls for the effects of stock market capitalization to GDP.

- *Panel E* controls for 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. All accounting figures are in U.S. 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 firm clustering. Significance levels are indicated by asterisks: *** for 1%, ** for 5%, and * for 10%.

Panel A: Index Estimated using Conventional PCA

	(1)	(2)	(3)	(4)
Dependent Var =	Total Investment		Capital Investment	
Conventional EFI Index $_{t-1}$	0.010***	0.009***	0.009***	0.008***
	(3.727)	(3.597)	(3.390)	(3.212)
Conventional EFI Index $_{t-1}$ × *Crisis*		0.005***		0.005***
		(4.023)		(4.330)
Firm FE + Year FE + Control Variables	Yes	Yes	Yes	Yes
Observations	44,499	44,499	44,499	44,499
Adjusted R^2	0.590	0.590	0.525	0.525

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

	(1)	(2)	(3)	(4)
Dependent Var =	Total Investment		Capital Investment	
P-PCA EFI Index $_{t-1}$	0.002	0.000	0.002	0.001
	(1.231)	(0.005)	(1.583)	(0.468)
P-PCA EFI Index $_{t-1}$ × *Crisis*		0.003***		0.002***
		(4.352)		(4.305)
Firm FE + Year FE + Control Variables	Yes	Yes	Yes	Yes
Observations	89,302	89,302	89,302	89,302
Adjusted R^2	0.640	0.641	0.514	0.515

Panel C: EFI Index 2-year prior to the Shock

	(1)	(2)	(3)	(4)
Dependent Var =	Total Investment		Capital Investment	
EFI Index $_{t-2}$	0.010***	0.008***	0.006**	0.005*
	(3.136)	(2.672)	(2.196)	(1.745)
EFI Index $_{t-2}$ × *Crisis*		0.005***		0.005***
		(5.368)		(5.230)
Firm FE + Year FE + Control Variables	Yes	Yes	Yes	Yes
Observations	89,197	89,197	89,197	89,197
Adjusted R^2	0.640	0.641	0.515	0.515

Panel D: Controlling for Stock Market Capitalization

	(1)	(2)	(3)	(4)
Dependent Var =	Total Investment		Capital Investment	
EFI Index $_{t-1}$	-0.001	-0.002	-0.007**	-0.007**
	(-0.352)	(-0.533)	(-2.015)	(-2.165)
EFI Index $_{t-1}$ × *Crisis*		0.005***		0.004***
		(5.272)		(4.786)
Stock market capitalization to GDP $_{t-1}$	0.001***	0.001***	0.001***	0.001***
	(3.878)	(3.274)	(3.782)	(3.267)
Firm FE + Year FE + Control Variables	Yes	Yes	Yes	Yes
Observations	59,387	59,387	59,387	59,387
Adjusted R^2	0.658	0.658	0.543	0.543

Panel E: Controlling for Macroeconomic Factors

	(1)	(2)	(3)	(4)
Dependent Var =	Total Investment		Capital Investment	
EFI Index $_{t-1}$	0.000	-0.001	0.002	0.001
	(0.151)	(-0.388)	(0.742)	(0.347)
EFI Index $_{t-1}$ × *Crisis*		0.005***		0.003***
		(4.174)		(3.052)
GDP Growth $_{t-1}$	-0.002	0.003	0.004	0.007
	(-0.308)	(0.591)	(0.757)	(1.390)
Inflation Rate $_{t-1}$	0.000	0.000	0.000	0.000
	(1.254)	(1.112)	(0.201)	(0.111)
Interest Rate $_{t-1}$	0.000**	0.000	0.000	0.000
	(2.153)	(0.829)	(1.493)	(0.576)
Firm FE + Year FE + Control Variables	Yes	Yes	Yes	Yes
Observations	57,481	57,481	57,481	57,481
Adjusted R^2	0.678	0.678	0.560	0.561

Table 6. Efficient Financial Institutions, External Financing Dependence, and Firm Investment

Note: This table presents regression estimates of firm investment on country-level EFI indices, based on a sample of Compustat Global firms from 2018 to 2021. The sample encompasses publicly listed firms from 55 economies. Excluded are financial firms, firm-year observations with non-positive book values of total assets or common equity, and those lacking the accounting information necessary for key variable construction. The EFI Index measures the efficiency of financial institutions. Total Investment is the ratio of annual total investment (the sum of capital expenditure and R&D expenditure) to the book value of total assets at the beginning of the fiscal year. 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. 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. All accounting figures are denominated in U.S. dollars, and all financial variables are winsorized at the 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 firm 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 =	(1) Total Investment	(2) Capital Investment
EFI Index $_{t-1}$	0.004	0.001
	(1.368)	(0.228)
EFI Index $_{t-1}$ × High External Fin Dependent	-0.002	0.005
	(-0.462)	(1.390)
EFI Index $_{t-1}$ × *Crisis*	0.001	0.002*
	(0.535)	(1.763)
EFI Index $_{t-1}$ × High External Fin Dependent × *Crisis*	0.006***	0.003**
	(3.259)	(2.126)
High External Fin Dependent × *Crisis*	-0.008***	-0.005***
	(-4.732)	(-3.495)
Control Variables	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	87,456	87,456
Adjusted R^2	0.642	0.516

Table 7. Efficient Financial Institutions, Bank Financing, and Firm Investment Evidence using Survey Data

Note: This table presents regression estimates of firm investment on country-level EFI indices using a sample of Compustat Global firms from 2018 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. Total Investment is the ratio of annual total investment (capital expenditure plus R&D expenditure) to the book value of total assets at the beginning of the fiscal year. Capital Investment is the ratio of annual capital expenditures 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. The percentage of firms using banks to finance purchases of fixed assets is used to identify firms that rely on banks for investment financing. This data is derived from the World Bank Enterprise Survey, a firm-level survey of a representative sample of an economy's private sector. High Bank Finance refers to the sample of countries that have above median percentage of firms using banks to finance purchases of fixed assets. Baseline controls and restrictions are included in all regressions. All accounting figures are in U.S. 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 firm 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)
Sample =	High Bank Finance Countries		Low Bank Finance Countries	
Dependent Var =	Total Investment	Capital Investment	Total Investment	Capital Investment
EFI Index $_{t-1}$	0.020***	0.019***	0.016	0.009
	(2.944)	(2.743)	(1.202)	(0.673)
EFI Index $_{t-1}$ × *Crisis*	0.009**	0.011***	0.014	0.018
	(2.326)	(2.711)	(1.142)	(1.502)
Control Variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	5,191	5,191	5,418	5,418
Adjusted R^2	0.526	0.477	0.602	0.477

Table 8. Efficient Financial Institutions, Collateral Assets, and Firm Investment

Note: This table presents regression estimates of firm investment on EFI indices based on a sample of Compustat Global firms from 2018 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. The EFI Index is a measure of efficiency in financial institutions. Total Investment is the ratio of annual total investment (comprising capital expenditure and R&D expenditure) to the book value of total assets at the beginning of the fiscal year. 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 accounting figures are denominated in U.S. dollars, and all financial variables are winsorized at 1st and 99th percentiles by country. All regressions incorporate firm and year-fixed effects. *T*-statistics enclosed in parentheses are based on standard errors adjusted for firm 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 =	(1) Total Investment	(2) Capital Investment	(3) Total Investment	(4) Capital Investment
EFI Index $_{t-1}$	0.001	0.003	0.004	0.002
	(0.433)	(1.337)	(0.660)	(0.440)
EFI Index $_{t-1}$ × *Crisis*	0.003***	0.002**	-0.005**	-0.003
	(2.923)	(2.346)	(-2.118)	(-1.239)
EFI Index $_{t-1}$ × High Tangibility $_{t-1}$	0.003	0.002		
	(1.193)	(0.720)		
EFI Index $_{t-1}$ × High Tangibility $_{t-1}$ × *Crisis*	0.003	0.004***		
	(1.556)	(2.685)		
High Tangibility $_{t-1}$ × *Crisis*	-0.014***	-0.016***		
	(-8.279)	(-10.378)		
High Tangibility $_{t-1}$	-0.006**	-0.003		
	(-2.426)	(-1.283)		
EFI Index $_{t-1}$ × Durability $_{t-1}$			-0.013*	-0.001
			(-1.788)	(-0.235)
EFI t-1 × Durability $_{t-1}$× *Crisis*			0.010***	0.005*
			(3.063)	(1.732)
Durability $_{t-1}$ × *Crisis*			-0.005	-0.000
			(-1.613)	(-0.171)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	89,301	89,301	26,446	26,446
Adjusted R^2	0.643	0.519	0.699	0.485

Table 9. Efficient Financial Institutions, Financial Constraints, and Firm Investment

Note: This table presents regression estimates of firm investment on country-level EFI indices using a sample of Compustat Global firms from 2018 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. Total Investment is the ratio of annual total investment (the sum of capital expenditure and R&D expenditure) to the book value of total assets at the beginning of the fiscal year. 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 INV-CF Sensitivity is a dummy variable that takes a value of 1 if the investment-to-cash flow sensitivity falls within the top tercile (by country-year) and 0 if it falls within the bottom tercile. High Cash-CF Sensitivity is a dummy variable that takes a value of 1 if the cash-to-cash flow sensitivity falls within the top tercile (by country-year) and 0 if it falls within the bottom tercile. All accounting figures are in U.S. 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 firm 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 =	(1) Total Investment	(2) Capital Investment	(3) Total Investment	(4) Capital Investment
EFI Index $_{t-1}$	-0.001	0.001	0.002	0.004
	(-0.174)	(0.255)	(0.533)	(1.083)
EFI Index $_{t-1}$ × *Crisis*	0.005***	0.004**	0.005**	0.005**
	(2.678)	(2.295)	(2.274)	(2.399)
EFI Index $_{t-1}$ × High INV-CF Sensitivity $_{t-1}$	0.009**	0.008**		
	(2.480)	(2.313)		
EFI Index $_{t-1}$ × High INV-CF Sensitivity $_{t-1}$ × *Crisis*	0.001	0.002		
	(0.240)	(0.921)		
High INV-CF t-1× *Crisis*	-0.003	-0.005**		
	(-1.391)	(-2.302)		
High INV-CF Sensitivity $_{t-1}$	-0.009**	-0.008**		
	(-2.568)	(-2.272)		
EFI Index $_{t-1}$ × High Cash-CF Sensitivity $_{t-1}$			0.004	0.003
			(1.194)	(1.121)
EFI Index $_{t-1}$ × High Cash-CF Sensitivity $_{t-1}$ × *Crisis*			0.002	0.001
			(0.648)	(0.480)
High Cash-CF Sensitivity $_{t-1}$ × *Crisis*			-0.000	-0.000
			(-0.123)	(-0.021)
High Cash -CF Sensitivity $_{t-1}$			-0.004	-0.003
			(-1.314)	(-0.934)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	42,231	42,231	41,979	41,979
Adjusted R^2	0.614	0.528	0.655	0.521

Table 10. Banking Efficiency, Exposure to the COVID-19 Shock, and Firm Investment

Note: This table presents regression estimates of yearly investment on country-level EFI indices based on a sample of Compustat Global firms from 2018 to 2021. The sample comprises publicly listed firms from 55 economies. 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 necessary for constructing key variables. Total Investment is the ratio of annual total investment (the sum of capital expenditure and R&D 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. Low COVID exposure markets are those with new COVID-19 cases (in 2020) below the median level. Low Government Support markets are those markets where the government economic support index is below the median. Non-resilient Industries are those industries with an affected share above the median. All accounting figures are in U.S. dollars, and all financial variables are winsorized at the 1st and 99th percentiles by country. All regressions include the baseline controls and restrictions. All regressions include firm and year-fixed effects. T-statistics in parentheses are based on standard errors adjusted for firm 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) High COVID exposure markets	(2) Low COVID exposure markets	(3) High Government Support	(4) Low Government Support	(5) Resilient Industries	(6) Non-resilient Industries
EFI Index $_{t-1}$	0.004	0.005	0.028***	-0.007***	-0.004	0.017***
	(1.165)	(1.151)	(5.765)	(-2.817)	(-0.828)	(3.263)
EFI Index $_{t-1}$ × *Crisis*	0.004***	0.004	0.002	0.003**	0.002	0.010***
	(3.891)	(1.412)	(1.042)	(2.201)	(0.837)	(4.942)
Control Variables	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Observations	49,528	39,773	36,521	52,780	25,539	15,729
Adjusted R^2	0.671	0.597	0.603	0.659	0.728	0.550

Table 11. 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 efficiency in financial institutions (EFI) controlling for quarterly GDP growth (In Panel B). EFI 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. The 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

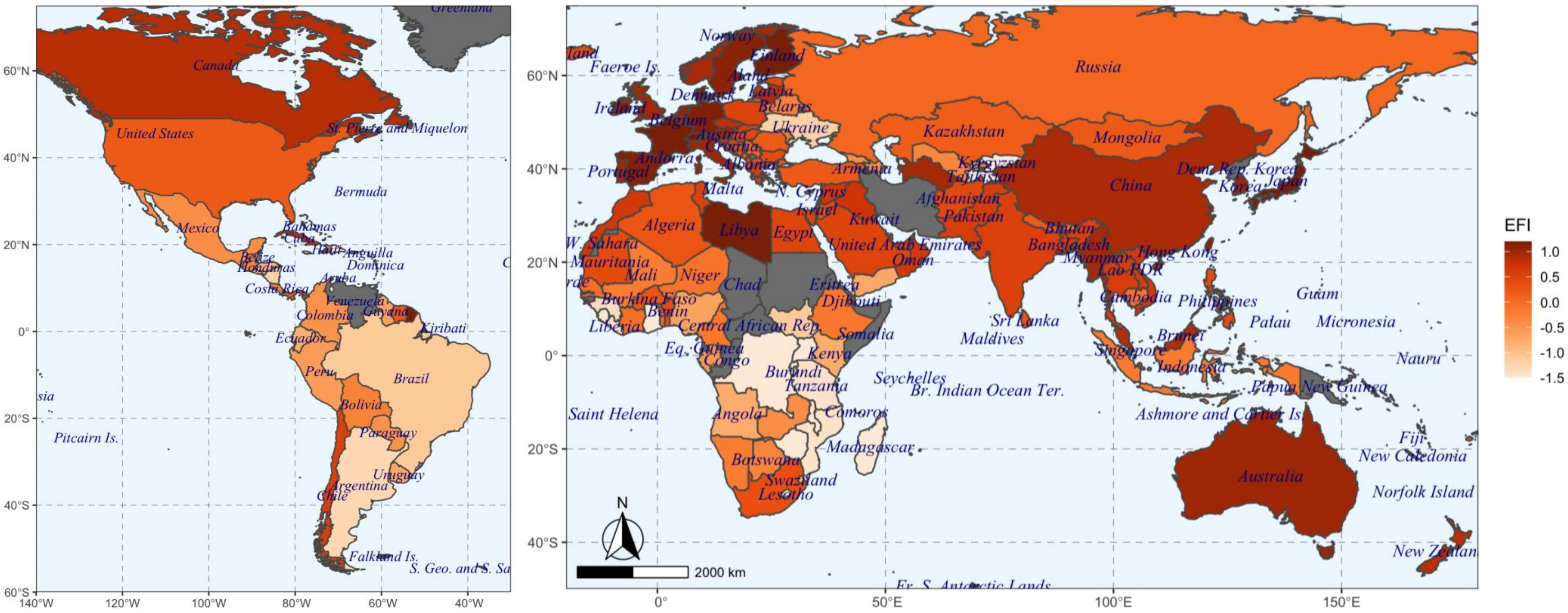
Panel B. Efficiency in Financial Intuitions and Credit Supply

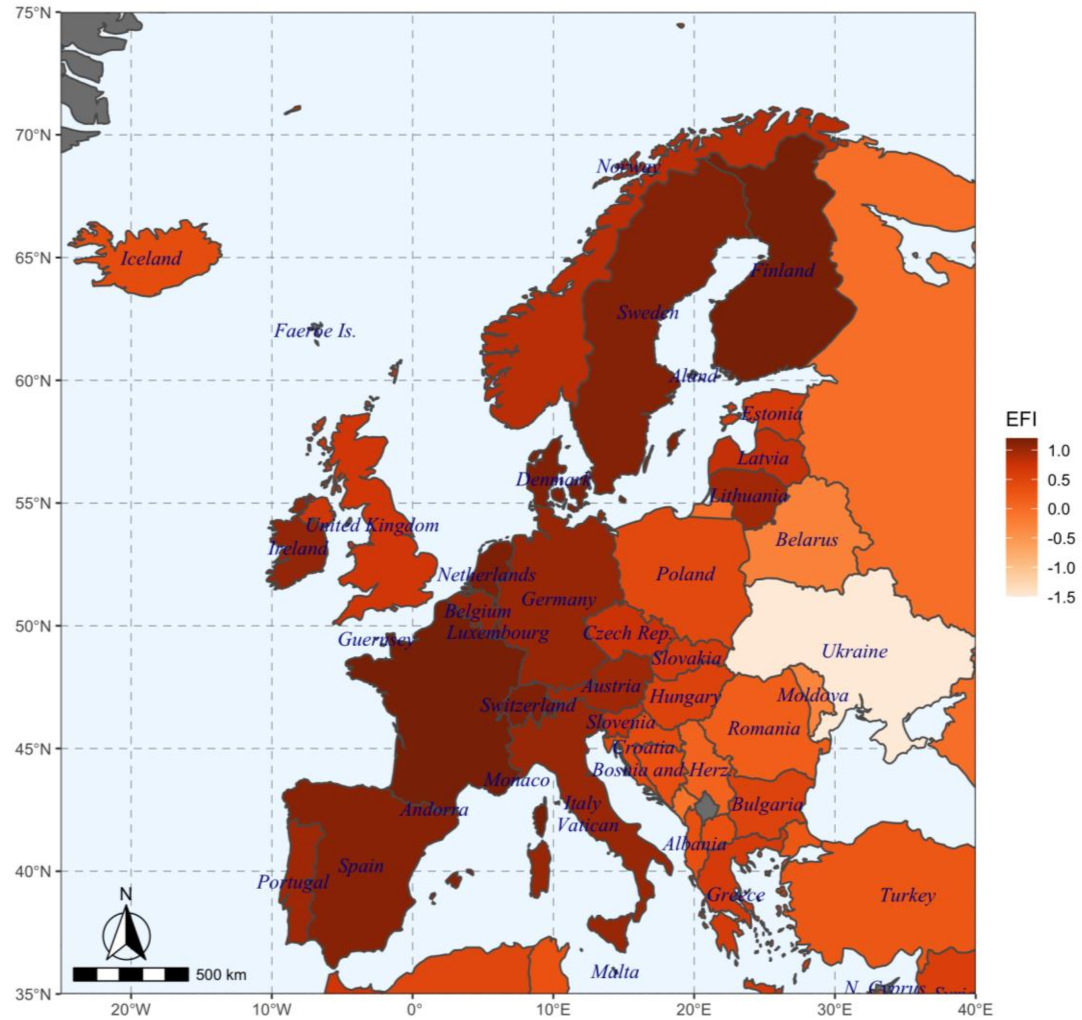
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var =	Bank Credit/GDP		Credit to Household/GDP		Credit to Corporation/GDP	
EFI Index $_{t-1}$	-4.873	-9.319***	-1.996	-3.485***	-0.648	-4.233*
	(-1.228)	(-3.767)	(-1.134)	(-2.850)	(-0.246)	(-1.803)
EFI Index $_{t-1}$ × *Crisis*		4.239***		1.420***		3.418***
		(6.587)		(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

Appendix

Figure A1. EFI Index in 2018

Note: This figure plots the Efficient Financial Institutions (EFI) index. EFI 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) average level of the EFI index.




EFI
1.0
0.5
0.0
-0.5
-1.0
-1.5
75°N
70°N
65°N
60°N
55°N
50°N
45°N
40°N
35°N
20°W
10°W
0°
10°E
20°E
30°E
40°E
N
500 km
Iceland
Faeroe Is.
Norway
Sweden
Finland
Aland
Estonia
Latvia
Lithuania
Denmark
United Kingdom
Ireland
Belarus
Netherlands
Poland
Germany
Belgium
Luxembourg
Guernsey
Czech Rep.
Slovakia
Ukraine
Austria
Hungary
Moldova
Switzerland
Slovenia
Romania
Croatia
Bosnia and Herz.
Monaco
Bulgaria
Andorra
Italy
Vatican
Albania
Spain
Portugal
Greece
Turkey
Malta

Continued.

Figure A2. EFI Broad Index: Bayesian Principal Components

Note: This figure plots the factor loadings from the Bayesian Principal Component Analysis (B-PCA) for the first two principal components. PC1 and PC2 are the 1st and 2nd principal components, respectively. The original crude efficiency 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, ei05 - bank's return on assets, ei06 – bank's return on equity, oi01 – bank concentration, and oi06 – five bank asset concentration. To compute the Broad EFI Index, we add the bank's return on equity, bank concentration, and five bank asset concentration to the baseline efficiency characteristics. Bank's return on equity is the commercial bank's after-tax net income to yearly averaged equity. Bank concentration is the assets of the three largest commercial banks as a share of total commercial banking assets. Five bank asset concentration is the assets of the five largest banks as a share of total commercial banking assets. The vectors represent the projected coordinate system for the original efficiency characteristics.

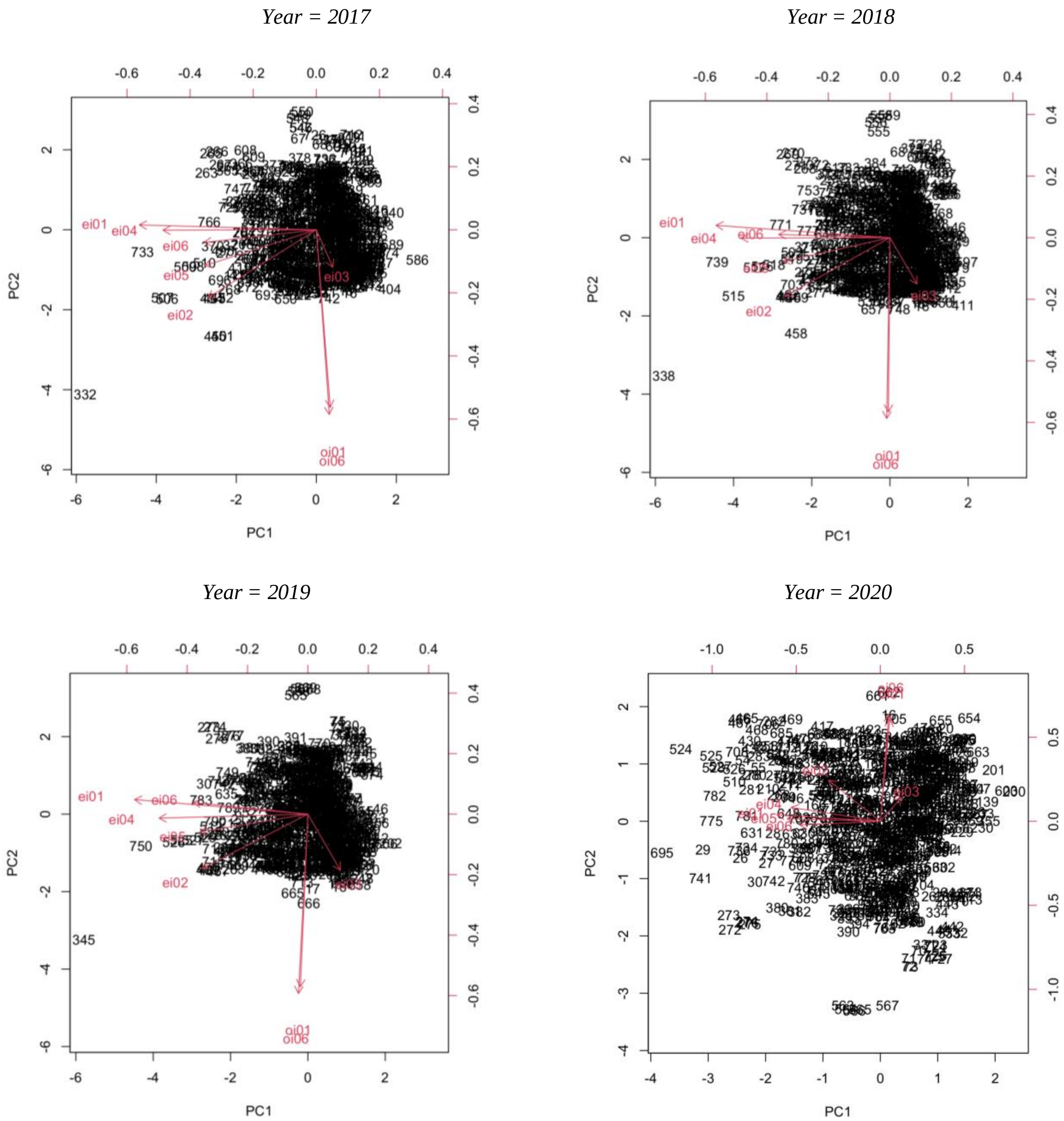
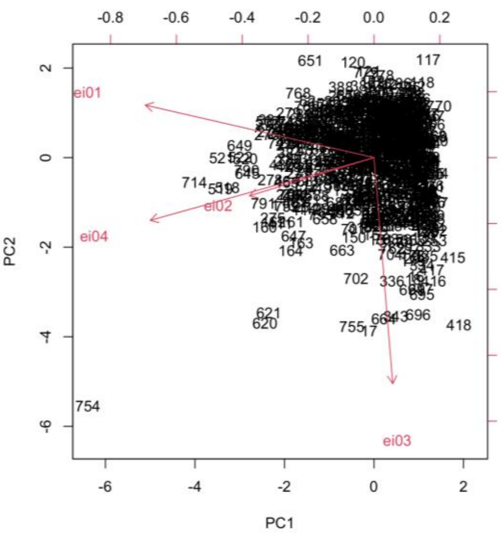


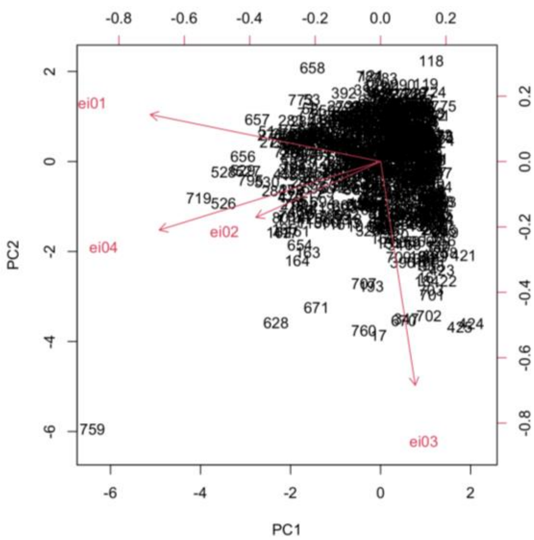
Figure A3. EFI Narrow Index: Bayesian Principal Components

Note: This figure plots the factor loadings from the Bayesian Principal Component Analysis (B-PCA) for the first two principal components. PC1 and PC2 are the 1st and 2nd principal components, respectively. The original crude efficiency characteristics are denoted in red: ei01 - net interest margin, ei02 - lending minus deposits spread, ei03 – noninterest income to total income, and ei04 - overhead costs to total assets. The vectors represent the projected coordinate system for the original efficiency characteristics.

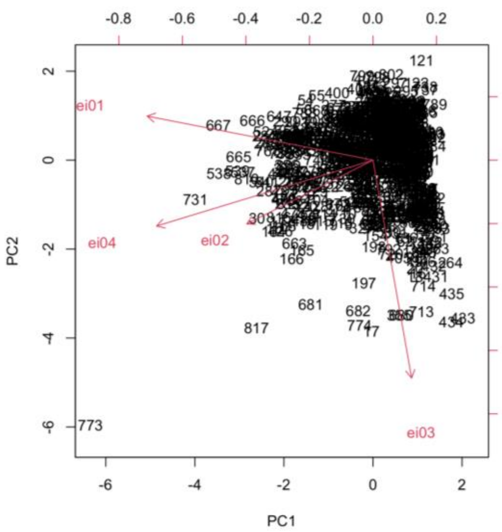
Year = 2017



Year = 2018



Year = 2019



Year = 2020

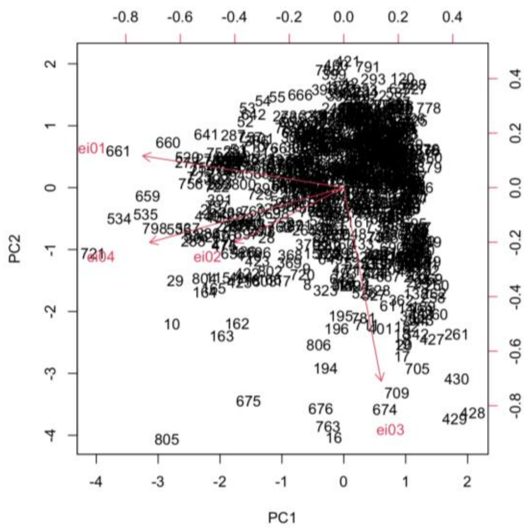


Figure A4. The proportion of Variance Explained by the EFI Index

Note: This figure plots the proportion of variance of the financial efficiency characteristics explained by the Index. We show the proportion of variance explained by the EFI Index, the EFI Broad Index, and the EFI Narrow Index. EFI Index is computed using a Bayesian treatment of the principal component analysis based on the net interest margin, lending minus deposits spread, noninterest income to total income, overhead costs to total assets, and the bank's return on assets. EFI Narrow Index is based on the net interest margin, lending minus deposits spread, noninterest income to total income, and overhead costs to total assets to compute the Bayesian principal components. EFI Broad Index is based on the net interest margin, lending minus deposits spread, noninterest income to total income, overhead costs to total assets, bank's return on assets, bank's return on equity, bank concentration, and five bank asset concentration to compute the Bayesian principal components.

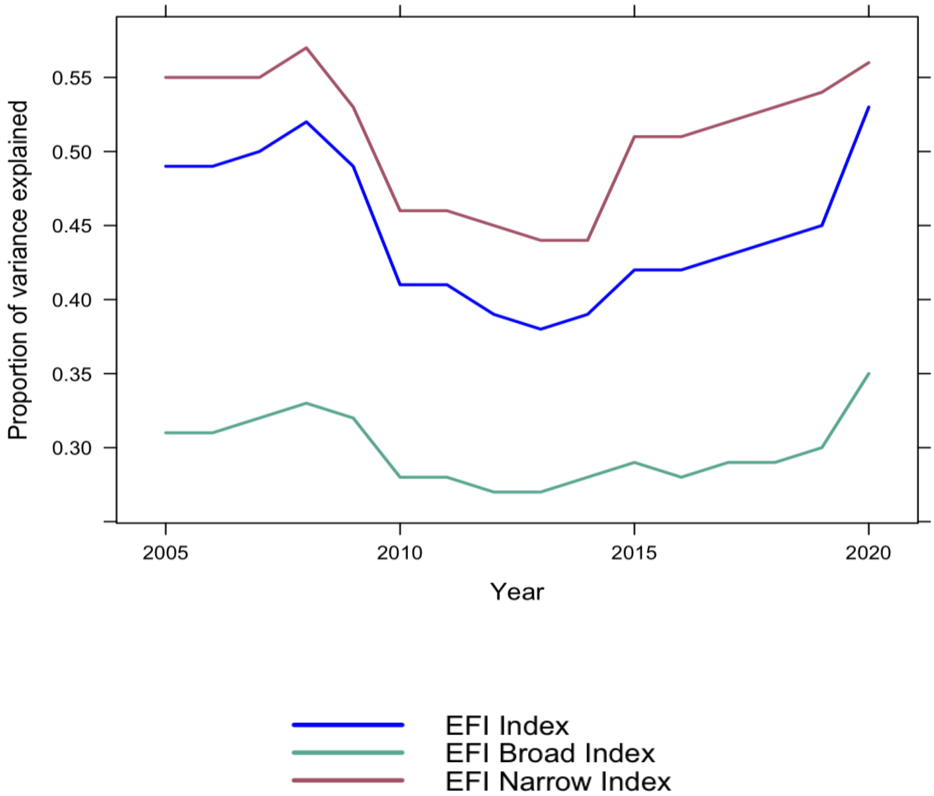


Table A1. Variable Description

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

Variable Name	Description	Source
EFI Index	The country-level index measuring the efficiency of banking institutions.	
Investment	Investment is the ratio of annual total investment (sum of capital expenditure and R&D expenditure) to the book value of total assets at the beginning of the fiscal year.	Compustat
CAPX/AT	the ratio of annual capital expenditure to book value of total assets at the beginning of the fiscal year.	Compustat
R&D/AT	the ratio of annual R&D 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 of GDP per capita.	IMF
Bank Credit/GDP	the ratio of total credit provided by banks to GDP per quarter	BIS
Credit to Household/GDP	the ratio of total credit provided to households to GDP per quarter	BIS
Credit to Corporation/GDP	the ratio of total credit provided to corporations to GDP per quarter	BIS

Table A2. IMF's FIE Index and Firm Investment

Note: This table presents regression estimates of yearly investment on IMF's financial institutions' efficiency (EFI) index based on a sample of Compustat Global firms from 2018 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. Total Investment is the ratio of annual total investment (sum of capital expenditure and R&D expenditure) to the book value of total assets at the beginning of the fiscal year. 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 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 firm clustering. Observations are the total number of firm-year observations. ***, **, *, indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Dependent Var =	Total Investment		Capital Investment	
IMF FIE Index $_{t-1}$	0.018	0.018	0.017	0.017
	(1.343)	(1.297)	(1.416)	(1.388)
IMF FIE Index $_{t-1}$ × *Crisis*		0.005		0.003
		(0.995)		(0.615)
Control Variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	89,302	89,302	89,302	89,302
Adjusted R^2	0.640	0.640	0.514	0.514

Table A3. EFI Index and Firm Investment: European Union Sub-Sample

Note: This table presents regression estimates of yearly investment on country-level EFI indices based on a sample of Compustat Global firms from 2018 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. EFI Index is computed using a simple 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. Total Investment is the ratio of annual total investment (sum of capital expenditure and R&D expenditure) to the book value of total assets at the beginning of the fiscal year. 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 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 firm 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	
EFI Index $_{t-1}$	0.006	0.001
	(0.871)	(0.097)
EFI Index $_{t-1}$ × *Crisis*		0.006*
		(1.940)
Control Variables	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	10,072	10,072
Adjusted R^2	0.502	0.502

Table A4. Efficient Financial Institutions and Firm Investment: Economic Development and Capital Regulations

Note: This table presents regression estimates of yearly investment on country-level EFI indices based on a sample of Compustat Global firms from 2018 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. EFI Index is the efficiency in financial institutions index. EFI Index is computed using a simple 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. Total Investment is the ratio of annual total investment (sum of capital expenditure and R&D expenditure) to the book value of total assets at the beginning of the fiscal year. 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. Developed or emerging markets are defined following MSCI. 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 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 firm clustering. Observations are the total number of firm-year observations. ***, **, *, indicate significance at the 1%, 5%, and 10% levels.

Dependent Var = Capital Investment	(1) Developed Markets	(2) Emerging Markets	(3) High Capital Stringency	(4) Low Capital Stringency
EFI Index $_{t-1}$	0.009***	0.006**	0.011***	-0.002
	(2.682)	(1.994)	(3.825)	(-0.798)
EFI Index $_{t-1}$ × *Crisis*	0.001	0.009***	0.005***	0.003***
	(1.324)	(5.736)	(3.420)	(3.198)
Control Variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	44,098	45,204	35,531	53,771
Adjusted R^2	0.552	0.484	0.479	0.561