Economics Letters 256 (2025) 112614

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Country-level cryptocurrency uncertainty and bank cost of capital

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ARTICLE INFO

Keywords:
Cryptocurrency uncertainty
Google trends
Cost of equity
Cost of debt
Bank competition
Default risk
Stability

ABSTRACT

This study explores the impact of country-level cryptocurrency uncertainty on bank cost of capital, utilizing data from 63 countries over the period of 2009 to 2023. Our findings indicate that cryptocurrency uncertainty is associated with a reduction in banks' cost of capital. This result remains robust using alternative proxies and controlling for endogeneity concerns. Additionally, we document that the impact is more pronounced for banks with low market competition, and high interest margin. These results provide valuable insights for policymakers and industry practitioners regarding the implications of cryptocurrency uncertainty on financial institutions.

1. Introduction

Since Bitcoin's launch in 2009, the cryptocurrency market has grown to over $3.92 trillion by 2024 (CoinGecko, 2025). Despite increasing adoption, cryptocurrencies remain highly volatile due to regulatory uncertainty, speculative trading, and technological risks (Ahmed et al., 2024; Farag et al., 2025). This volatility has raised concerns about its impact on financial markets, particularly the traditional banking sector. Cryptocurrency risks may affect banks' ability to raise capital by transmitting adverse shocks from the cryptocurrency market to broader financial markets, including stocks, bonds, exchange rates, and volatility indices, as shown by Vuković et al. (2025). Such spillovers can increase risk premiums and raise banks' cost of capital. At the same time, heightened cryptocurrency uncertainty may also reduce capital costs if investors shift funds toward traditional banks perceived as safer, or if regulatory and financial innovations strengthen the relative position of banks (Adela, 2025; Auer and Claessens, 2021). While studies have explored cryptocurrency volatility's impact on financial markets (Baur et al., 2018) fewer have examined its effects on banks' financing costs.

The cost of capital, encompassing both equity and debt financing, is a key determinant of banks' stability and competitive strength. Periods of heightened cryptocurrency uncertainty often trigger a reallocation of investor portfolios away from speculative assets and toward safer institutions. Traditional banks, with their relatively stable business models and regulatory safeguards, become natural beneficiaries of this "flight to safety," as deposits and bank debt are perceived as secure stores of value. This increased demand for bank liabilities reduces the returns required by investors, thereby lowering banks' cost of capital. Building on this intuition, we hypothesize that cryptocurrency uncertainty lowers the cost of capital for banks.

This study contributes to the literature in several important ways. First, while most research on cryptocurrencies has focused on asset-level dynamics (Baur et al., 2018; Farag et al., 2025; Urquhart, 2018), we extend the discussion to the banking sector by examining how cryptocurrency uncertainty affects banks' cost of capital. Second, we construct a country-level cryptocurrency uncertainty index using Google Trends, offering a novel way to capture market sentiment. Our approach complements recent work on cryptocurrency price differences across countries, which also provide country-level measures of activity and risk in crypto markets (Borri and Shakhnov 2023; Makarov and Schoar, 2020). For example, Borri and Shakhnov (2023) propose using the volatility of Bitcoin price differences across markets as a proxy for country-specific uncertainty. Finally, our channel analysis, focusing on market competition and interest margins, provides insights that can guide policymakers and regulators in developing strategies to manage the risks that cryptocurrency uncertainty poses for the banking sector.

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https://doi.org/10.1016/j.econlet.2025.112614
Received 10 July 2025; Received in revised form 1 September 2025; Accepted 11 September 2025
Available online 11 September 2025

2. Data and methodology

2.1. Measuring cryptocurrency uncertainty

Cryptocurrency uncertainty can be measured through various approaches. For instance, Lucey et al. (2022) utilized a news-based dataset to construct weekly indices capturing both cryptocurrency policy and price uncertainty. However, this measure reflects aggregated uncertainty at the global level and may not fully capture country-specific dynamics. An alternative method involves analyzing internet search behavior. High volumes of internet searches often signal heightened public interest, which may be driven by anxiety, uncertainty, or heightened attention (Boungou and Yatié, 2022). Drawing on this intuition, several studies have employed Google Trends data to measure uncertainty in macroeconomic (Bilgin et al., 2019; Castelnuovo and Tran, 2017) and other contexts (Szczygielski et al., 2024).

Following this approach, we use Google Trends data to construct a Country-level Cryptocurrency Uncertainty Index (CCUI). Specifically, following earlier studies (Aslanidis et al., 2022; Castelnuovo and Tran, 2017; Urquhart, 2018) we select a set of relevant keywords related to cryptocurrencies and apply Principal Component Analysis (PCA) to extract a common factor representing overall uncertainty.[1] The resulting index is normalized to a scale from 0 to 1, where higher values reflect greater uncertainty. We then compute the yearly average of the monthly index values to obtain an annual measure of cryptocurrency uncertainty.

Following Borri and Shakhnov (2023), we also use a volatility-based measure of cryptocurrency uncertainty.[2]

2.2. Measuring cost of capital

To capture the cost of capital from multiple dimensions, we employ four distinct measures[3] (Acheampong and Ibeji, 2024). First, the Weighted Average Cost of Capital (WACC) reflects the overall cost of financing from both equity and debt sources. Second, the Cost of Equity Capital (WACC_EQ) isolates the return required by equity investors. Third, the Cost of Debt Capital (WACC_DEBT) represents the effective interest rate paid on borrowed funds. Lastly, we include Return on Capital scaled by WACC (ROC_WACC) to assess the efficiency of capital use relative to its cost.

2.3. Regression model

To test our hypothesis that cryptocurrency uncertainty reduces banks' cost of capital, we employ the following OLS model:

$$\begin{aligned}\text{Cost of Capital}_{c,i,t} = {} & \beta_0 + \beta_1 CCUI_{c,t} + \sum \gamma_k Bank - level\ Controls_{c,i,t} \\ & + \sum \lambda_k Macro\ Controls_{c,t} + BankFE + YearFE \\ & + \varepsilon_{c,i,t} \end{aligned} \tag{1}$$

Here Cost of Capital$_{c,i,t}$, is the cost of capital proxies, WACC, WACC_EQ, WACC_DEBT, and ROC_WACC for bank i of country c at year t. $CCUI_{c,t}$ denotes country-level cryptocurrency uncertainty index for country c at year t. Following earlier studies, we also control for $Bank - level\ Controls_{c,i,t}$ and $Macro\ Controls_{c,t}$ in our model.[4] Furthermore, we also consider bank and year level fixed effects which are denoted by *BankFE* and *YearFE*. $\varepsilon_{c,i,t}$ denote error term.

3. Data and sample

We begin constructing our dataset by collecting bank-level data from Bloomberg for publicly listed banks. We then gather Google Trends data and macroeconomic variables from the World Bank and LSEG Workspace. After removing missing observations, we obtain a dataset comprising 11,485 bank-year observations across 63 countries,[5] covering the period from 2009 to 2023. To reduce the influence of outliers, all variables a are winsorized at the 1st and 99th percentiles. Summary statistics are presented in Appendix D (Table D.1).

4. Empirical results

4.1. Baseline results

Table 1 displays the results of the baseline regression analysis. In all models, CCUI is included as the primary independent variable. The results indicate that the coefficient for CCUI is negative and statistically significant across all models. This finding is also economically significant, for instance, in Model 3, a one standard deviation increase in CCUI leads to a decrease in the cost of equity by 8.298 %[6].

This result can be explained by the fact that cryptocurrency uncertainty encourages investors to reallocate their portfolios toward safer assets, such as bank deposits and debt instruments (Adela, 2025; Baur et al., 2018). As uncertainty in cryptocurrency markets rises, traditional banks are perceived as relatively more stable and secure, which increases the demand for their liabilities. This greater demand lowers the required returns on bank equity and debt, thereby reducing banks' overall cost of capital.

4.2. Robustness test results

In this section, we assess the robustness of our results by using alternative proxies. Table 2, Panel A presents the findings for alternative proxies for bank cost of capital. The results show that the coefficient of CCUI is negative for WACC, indicating that cryptocurrency uncertainty reduces the overall cost of capital. In contrast, the coefficient for ROC_WACC is positive, suggesting that cryptocurrency uncertainty increases the return on invested capital. Furthermore, Table 2, Panel B presents the findings using an alternative proxy for cryptocurrency uncertainty and shows that the coefficient of CCUI_VOL is negative and significant. These findings reinforce our initial results, providing strong support for the robustness of our baseline conclusions.

[1] The list of selected keywords is presented in Appendix A. Google Trends data for each keyword and country were collected using the "trendecon" R package.

[2] Following Borri and Shakhnov (2023), we collect local bitcoin price series for the sampled countries using CryptoCompare as the primary source. For each country we map its currency and retrieve daily close prices for BTC quoted in that currency on exchanges operating in the country or region, prioritizing local venues and then global majors. When no venue level series is available, we use the CryptoCompare composite as fallback. Finally, volatility-based country-level cryptocurrency uncertainty is measured. Daily volatility is estimated from Bitcoin returns using a GARCH model, and the annual average is then calculated.

[3] All measures of cost of capital are collected from Bloomberg.

[4] See Appendix B for detailed description of all variables. At bank level, we consider natural logarithm of total assets (SIZE), non-interest income scaled by the sum of interest and non-interest income (NNID), total loans scaled by total deposits (LDR), total loans scaled by total assets (LIQ), the dividend payout ratio (DPR), the asset-to-equity ratio (AE), return on assets (ROA), the market value to total assets ratio (TOBINSQ), and cash flow from operations scaled by total assets (CASH_FLOW). At the macro level, we control for country-specific financial and economic conditions using the loan-to-GDP ratio (LOAN_GDP), GDP growth rate (GDPG), the lending interest rate (LIR), and inflation (INF). We also include stock market volatility (MKT_VOL), measured as the logarithm of market index return volatility estimated with a GARCH model.

[5] List of sampled banks are presented in Appendix C.

[6] Calculated as $-8.298\% = (-2.767\times0.287)/9.570$.

Table 1
Baseline regression results.

VARIABLES	(1) WACC_EQ	(2) WACC_EQ	(3) WACC_EQ	(4) WACC_DEBT	(5) WACC_DEBT	(6) WACC_DEBT
CCUI	−2.965***	−2.733***	−2.767***	−1.871***	−1.134***	−0.994***
	(0.126)	(0.186)	(0.198)	(0.085)	(0.087)	(0.088)
SIZE			0.080			0.161***
			(0.090)			(0.047)
NNID			−0.666***			−1.103***
			(0.206)			(0.110)
LDR			−0.126			0.336***
			(0.219)			(0.109)
LIQ			−0.163			−0.343
			(0.481)			(0.232)
DPR			−0.002			0.000
			(0.001)			(0.001)
AE			−0.015			0.048***
			(0.014)			(0.007)
ROA			−0.083			0.101***
			(0.066)			(0.034)
TOBINSQ			−0.267			0.049
			(0.320)			(0.152)
CASH_FLOW			0.013*			−0.002
			(0.007)			(0.004)
LOAN_GDP			−0.012***			0.001
			(0.004)			(0.002)
GDPG			0.006			0.005
			(0.007)			(0.003)
LIR			0.072***			−0.039***
			(0.017)			(0.008)
INF			0.007			−0.002
			(0.006)			(0.001)
MKT_VOL			−0.062			0.117***
			(0.068)			(0.033)
Constant	11.756***	11.582***	12.551***	3.925***	3.379***	1.367***
	(0.101)	(0.140)	(1.012)	(0.072)	(0.066)	(0.509)
Observations	10,807	10,787	10,787	11,485	11,485	11,485
R-squared	0.049	0.749	0.751	0.052	0.835	0.841
Bank FE	NO	YES	YES	NO	YES	YES
Year FE	NO	YES	YES	NO	YES	YES

Note: This table shows the results of the baseline regression analysis. Models 1, 2, 4 and 5 are bivariate, while Models 3 and 6 are multivariate, incorporating both bank-level and macroeconomic controls. Models 1, 2, and 3 use WACC_EQ as the dependent variable, whereas Models 4, 5, and 4 use WACC_DEBT as the dependent variable. All models include CCUI as the main independent variable. Robust standard errors are reported in brackets. Descriptions of all variables are provided in Table B.1. *** indicates significance at the 1 % level, ** at the 5 % level, and * at the 10 % level.

4.3. Endogeneity concerns

In this section, we address potential endogeneity concerns. First, we employ two-stage least squares (2SLS) model. The 2SLS approach helps mitigate endogeneity by using an instrumental variable (IV) that is correlated with the endogenous explanatory variable (cryptocurrency uncertainty) but uncorrelated with the error term in the regression. We use the average global cryptocurrency uncertainty, excluding the local country (AVG_CCUI), as our instrumental variable. It is correlated with country-level cryptocurrency uncertainty but shows no evidence of correlation with bank-level cost of capital. Table 3, Panel A presents the results from the instrumental variable regression. The first stage regression shows a statistically significant positive coefficient for AVG_CCUI. In the second stage, the coefficient of the fitted CCUI is negative and statistically significant.[7] These results suggest that our findings are not biased by endogeneity concerns.

Next, we employ Propensity Score Matching (PSM) and Entropy Balancing (EB) to mitigate sample selection bias. PSM works by matching treated and control units with similar characteristics based on the propensity score, reducing selection bias by ensuring that the treatment and control groups are comparable (Rosenbaum and Rubin, 1983). EB, on the other hand, weights the sample to balance the distribution of covariates across treatment and control groups (Hainmueller, 2012). The treatment and control groups are defined using a dummy variable based on the median value of CCUI. Table 3, Panel B presents the results for the PSM and EB-matched sample. The results show a consistent negative coefficient for CCUI, which further corroborates our initial findings, supporting the robustness of our conclusions.

Finally, we use a difference-in-differences (DiD) regression to examine a quasi-natural experiment involving external shocks in the cryptocurrency market. Specifically, we consider the interaction effects of two significant events: MT_GOX and HACK_2018.[8] The results in Table 3, Panel C show that the coefficients for CCUI and the interaction terms CCUI × MT_GOX and CCUI × HACK_2018 are all negative and statistically significant. These findings suggest that our results are not biased by external shocks, further corroborating the robustness of our initial conclusions.

[7] Diagnostic tests, including the Kleibergen-Paap rk LM statistic, the Kleibergen-Paap Wald rk F statistic, and the Anderson-Rubin Wald test, all fall within acceptable thresholds.

[8] MT_GOX, a dummy variable for the Mt. Gox hack in 2015 (where the value is 1 from 2015 onward, otherwise 0), and HACK_2018, a dummy variable for the Coincheck hack in 2018 (where the value is 1 from 2018 onward, otherwise 0)

Table 2
Robustness test results.
Panel A: Robustness test using alternative proxies of cost of capital.

VARIABLES	(1) WACC	(2) ROC_WACC
CCUI	−2.223***	0.355***
	(0.151)	(0.047)
Constant	8.338***	−0.334
	(0.806)	(0.269)
Observations	11,485	11,485
R-squared	0.783	0.650
Bank FE	YES	YES
Year FE	YES	YES
Controls	YES	YES

Panel B: Robustness test using alternative proxy of country-level cryptocurrency uncertainty.

	(1)	(2)
VARIABLES	WACC_EQ	WACC_DEBT
CCUI_VOL	−0.078***	−0.022***
	(0.011)	(0.006)
Constant	13.824***	1.308***
	(0.996)	(0.486)
Observations	10,787	11,485
R-squared	0.698	0.782
Bank FE	YES	YES
Year FE	YES	YES
Controls	YES	YES

Note: This table reports the results of the robustness analysis. Panel A presents the results using alternative proxies for the cost of capital, while Panel B presents the results using an alternative proxy for country-level cryptocurrency uncertainty. Robust standard errors are reported in brackets, and all models control for bank and year fixed effects. Descriptions of all variables are provided in Table B.1. *** indicates significance at the 1 % level, ** at the 5 % level, and * at the 10 % level.

5. Channel analysis

In this section, we explore the potential channels through which cryptocurrency uncertainty impacts banks' cost of capital, focusing on market competition and interest margin. Previous studies suggest that that cost of capital is linked to factors like market competition, and interest margin (Chen, 2022; Gleißner, 2019; Yin, 2021). We hypothesize that during periods of heightened uncertainty, the impact of cryptocurrency uncertainty is more pronounced for banks with low market competition, high interest margin[9]. Table 4 presents the results from our channel analysis. The coefficients for the interaction terms CCUI × Low Market Competition and CCUI × High Net Interest Margin are more pronounced, supporting our conjecture. These results indicate that cryptocurrency uncertainty disproportionately affects banks with less competitive pressure and higher interest margin, suggesting that such banks are more sensitive to market disruptions and shifts in investor sentiment (Vuković et al., 2025; Auer and Claessens, 2021). This aligns with the view that less competitive and more stable banks face greater capital cost adjustments during times of uncertainty.

6. Conclusions

This study examines the impact of cryptocurrency uncertainty on bank cost of capital. We find that cryptocurrency uncertainty is linked to a reduction in banks' cost of capital. This result remains robust even when using alternative proxies and controlling for endogeneity. Additionally, the association is more pronounced for banks with low market competition and high interest margin. Based on these findings, regulators, policymakers, and industry practitioners should create policies to address cryptocurrency uncertainty, such as enhancing digital asset regulations, promoting less banking competition, and implementing risk management frameworks to ensure banks remain resilient and safeguard financial stability.

Table 3
Endogeneity concern results
Panel A: Instrumental variable regression results.

VARIABLES	(1) CCUI	(2) WACC_EQ	(3) WACC_DEBT
AVG_CCUI	0.913***		
	(0.025)		
Fitted CCUI		−6.486***	−6.116***
		(0.490)	(0.323)
Observations	10,787	7364	8030
R-squared		0.117	0.358
Bank FE	YES	YES	YES
Year FE	NO	NO	NO
Controls	YES	YES	YES
Kleibergen-Paap rk LM statistic	986.890***		
Kleibergen-Paap Wald rk F statistic	1313.960		
Anderson-Rubin Wald test	312.68***		

Panel B: PSM and EB matched sample results.

	(1) PSM Matched sample	(2) EB Matched sample	(3)	(4)
VARIABLES	WACC_EQ	WACC_DEBT	WACC_EQ	WACC_DEBT
CCUI	−2.127***	−0.477***	−2.789***	−0.682***
	(0.278)	(0.119)	(0.183)	(0.087)
Constant	11.775***	0.201	11.760***	0.303
	(1.266)	(0.614)	(0.893)	(0.510)
Observations	7583	8037	10,787	11,485
R-squared	0.788	0.853	0.756	0.840
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES

Panel C: Quasi natural experiment results.

VARIABLES	(1) WACC_EQ	(2) WACC_DEBT	(3) WACC_EQ	(4) WACC_DEBT
CCUI	−2.879***	−0.756***	−3.239***	−0.958***
	(0.237)	(0.115)	(0.185)	(0.087)
MT_GOX	−1.074***	−0.164*		
	(0.197)	(0.097)		
CCUI × MT_GOX	−0.965***	−0.243**		
	(0.209)	(0.102)		
HACK_2018			0.825***	−0.009
			(0.176)	(0.081)
CCUI × HACK_2018			−1.995***	−0.248**
			(0.224)	(0.107)
Constant	16.817***	2.547***	19.582***	2.818***
	(0.916)	(0.490)	(0.975)	(0.499)
Observations	10,787	11,485	10,787	11,485
R-squared	0.732	0.786	0.717	0.785
Bank FE	YES	YES	YES	YES
Year FE	NO	NO	YES	YES
Controls	YES	YES	YES	YES

Note: This table shows the results of endogeneity concern. Panel A shows result for instrumental variable regression results, where AVG_CCUI is used as instrumental variable. Panel B shows PSM and EB matched sample results. The treatment and control groups are defined using a dummy variable, which is created based on the median value of CCUI. Panel C shows quasi natural experiment results based on MT_GOX and HACK_2018. Robust standard errors are reported in brackets. Descriptions of all variables are provided in Table B.1. *** indicates significance at the 1 % level, ** at the 5 % level, and * at the 10 % level.

[9] See Table B.1 for detailed description of low market competition and high net interest margin.

Table 4
Channel analysis results.

VARIABLES	(1) WACC_EQ	(2) WACC_DEBT	(3) WACC_EQ	(4) WACC_DEBT
CCUI	−2.263***	−0.895***	−2.311***	−0.695***
	(0.236)	(0.110)	(0.237)	(0.097)
Low Market Competition	1.062***	0.201*		
	(0.225)	(0.121)		
CCUI × Low Market Competition	−1.176***	−0.234*		
	(0.240)	(0.124)		
High Net Interest Margin			0.822***	0.295***
			(0.210)	(0.085)
CCUI × High Net Interest Margin			−0.793***	−0.479***
			(0.243)	(0.100)
Constant	12.383***	1.332***	12.088***	1.251**
	(1.018)	(0.507)	(1.045)	(0.523)
Observations	10,787	11,485	10,222	10,880
R-squared	0.752	0.841	0.755	0.842
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES

Note: This table shows the results of channel analysis. We consider Low Market Competition and high net interest margin as channel variable. All models include CCUI as the main independent variable. Robust standard errors are reported in brackets, and all models control for bank and year fixed effects. Descriptions of all variables are provided in Table B.1. *** indicates significance at the 1 % level, ** at the 5 % level, and * at the 10 % level.

Declaration of competing interest

on behalf of all authors, the corresponding author states no conflict of interest.

Appendix A

Cryptocurrency uncertainty index keywords: "Bitcoin uncertainty", "BTC uncertainty", "ETH uncertainty", "Solana uncertainty", "Ethereum uncertainty", "Ripple uncertainty", "Doge Coin uncertainty", "Litecoin uncertainty", "Tether uncertainty", "Cryptocurrency uncertainty", "Cryptocurrencies uncertainty", "NFT uncertainty", "DeFi uncertainty", "Bitcoin regulation", "BTC regulation", "ETH regulation", "Solana regulation", "Ethereum regulation", "Ripple regulation", "Doge Coin regulation", "Litecoin regulation", "Tether regulation", "Cryptocurrency regulation", "Cryptocurrencies regulation", "NFT regulation", "DeFi regulation", "Bitcoin policy", "BTC policy", "ETH policy", "Solana policy", "Ethereum policy", "Ripple policy", "Doge Coin policy", "Litecoin policy", "Tether policy", "Cryptocurrency policy", "Cryptocurrencies policy", "NFT policy", "DeFi policy", "Bitcoin", "BTC", "ETH", "Solana", "Ethereum", "Ripple", "Doge Coin", "Litecoin", "Tether", "Cryptocurrency", and "Cryptocurrencies".

Appendix B

Table B.1
Variable specification.

Variable	Description	Data Source
Panel A: Dependent variables		
WACC	Weighted average cost of capital	Bloomberg
WACC_EQ	Cost of equity capital	Bloomberg
WACC_DEBT	Cost of debt capital	Bloomberg
ROC_WACC	Return on capital scaled by weighted average cost of capital	Bloomberg
Panel B: Independent variables		
CCUI	Country-level cryptocurrency uncertainty index measured using first principal component analysis of related keywords Google Trends. Values are normalized between 0 and 1. See Appendix A for keyword list.	Authors calculation from Google Trends
CCUI_VOL	Volatility-based country-level cryptocurrency uncertainty is measured using Bitcoin prices from each country’s or region’s cryptocurrency exchange in local currency. Daily volatility is estimated from Bitcoin returns using a GARCH model, and the annual average is then calculated.	Authors Calculation from cryptocompare.com
Panel C: Bank-level control variables		
SIZE	Natural logarithm of bank total assets	Bloomberg
NNID	Non-interest income scaled by the sum of interest-and non-interest incomes	Bloomberg
LDR	Total loan scaled by total deposit	Bloomberg
LIQ	Total loans scaled by total assets	Bloomberg
DPR	Dividend payout ratio	Bloomberg
AE	Asset to equity ratio	Bloomberg
ROA	Return on assets	Bloomberg
TOBINSQ	Market value to total assets	Bloomberg

(*continued on next page*)

Table B.1 (*continued*)

Variable	Description	Data Source
CASH_FLOW	Cashflow flow from operations scaled by total assets	Bloomberg
Panel D: Macro-level control variables		
LOAN_GDP	Country level loan to GDP ratio	The World Bank
GDPG	Annual GDP growth rate	The World Bank
LIR	Lending interest rate	The World Bank
INF	Inflation	The World Bank
MKT_VOL	Natural logarithm of stock market volatility. Stock market volatility is measured using the daily return series of each country's market index, estimated with a GARCH model. The annual average of these estimates is used to measure annual volatility.	LSEG Workspace
Panel E: Other variables		
MT_GOX	Dummy variable for Mt. Gox hack in 2015, where value is 1 onward 2015 otherwise 0.	Authors Calculation
HACK_2018	Dummy variable for Coincheck hack in 2018, where value is 1 onward 2015 otherwise 0.	Authors Calculation
Low Market Competition	Low market competition is dummy variable where value is 1 if the value of loan Herfindahl-Hirschman Index (HHI) is less than the median loan HHI, otherwise 0.	Bloomberg
High Net Interest Margin	High net interest margin is dummy variable where value is 1 if the value of net interest margin is higher than the median net interest margin, otherwise 0.	Bloomberg

Appendix C

List of sample countries ISO codes: "AE, AR, AT, AU, BD, BE, BH, BR, BW, CA, CH, CL, CN, CO, CZ, DE, DK, EE, EG, ES, FI, FR, GB, GR, HR, HU, ID, IL, IN, IT, JO, JP, KE, KR, KW, KZ, LB, LK, MA, MU, MX, MY, NG, NL, NO, OM, PA, PE, pH, PK, QA, RO, RU, SA, SE, SG, SI, TH, UA, UG, US, VN, and ZA".

Appendix D

Table D.1
Summary statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
WACC	11,485	5.966	3.234	0.846	15.020
WACC_EQ	10,807	9.570	3.872	3.250	20.073
WACC_DEBT	11,485	2.541	2.358	0.000	10.652
ROC_WACC	11,485	1.236	0.908	−0.629	4.537
CCUI	11,485	0.740	0.287	0.000	1.000
CCUI_VOL	11,485	2.232	3.631	0.000	14.903
SIZE	11,485	8.991	1.858	5.195	12.116
NNID	11,485	0.346	0.240	0.044	0.953
LDR	11,485	0.925	0.317	0.460	1.891
LIQ	11,485	0.637	0.140	0.328	0.874
DPR	11,485	30.686	24.665	0.000	85.849
AE	11,485	11.212	4.357	4.655	21.811
ROA	11,485	1.027	0.689	−0.366	2.980
TOBINSQ	11,485	1.027	0.071	0.935	1.213
CASH_FLOW	11,485	1.369	3.612	−7.308	10.206
LOAN_GDP	11,485	82.047	49.191	10.779	239.519
GDPG	11,485	2.916	3.213	−21.400	26.170
LIR	11,485	4.936	4.398	0.000	16.792
INF	11,485	3.691	5.825	−4.863	221.342
MKT_VOL	11,485	1.214	0.540	0.000	5.898

Data availability

Data will be made available on request.

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