Does Sovereign Default Risk Explain Cryptocurrency Adoption? International Evidence from Mobile Apps

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Abstract

We study the macroeconomic drivers of cryptocurrency adoption using mobile app data for G20 countries. We find that sovereign default risk is a key driver. In penalized panel regressions, a 10% increase in sovereign CDS spreads is associated with a 2.8-3.6% increase in crypto app usage and downloads. These effects are larger in emerging markets and when the social cost of default (SCD) is high. Event studies show a significant increase in crypto adoption after sovereign credit events associated with large CDS jumps and rating downgrades, including events associated with high inflation, high SCD, and high political instability. Finally, we find that the effect of inflation on crypto adoption is non-linear and depends on the SCD.

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1 Introduction

The rapid growth and globalization of cryptocurrencies raises new questions about the underlying factors driving crypto adoption around the world.[1] For example, using bitcoin or non-domestic stablecoins to hedge domestic macroeconomic risks such as government or monetary instability is a frequently argued narrative in public discourse. These debates were traditionally reserved for developing countries where household investment and savings decisions explicitly take such risks into consideration. But more recently, these issues are increasingly discussed among advanced economies. In 2024, the US Congress even proposed legislation to introduce a 'Strategic Bitcoin Reserve' for reasons including "to provide a hedge against economic uncertainty and monetary instability". Despite growing interest in these narratives, empirical support for such claims is limited.[2]

This paper studies the macroeconomic drivers of crypto adoption with a specific focus on sovereign risk. While many studies explore the macroeconomic drivers cryptocurrency adoption, they often use single-country surveys or micro-data [Auer and Tercero-Lucas, 2022; Hackethal et al., 2022; Aiello et al., 2023; Weber et al., 2023; Benetton and Compiani, 2024; Cong et al., 2024]. However, it is difficult to compare the economic importance of various macroeconomic factors in cryptocurrency adoption without cross-country variation. Using an international panel dataset, we examine how country-level factors shape households' decisions to adopt cryptocurrencies and, in particular, whether the proposed drivers are solely

[1] Cryptocurrencies represent digital tokens that can be self-custodied and whose transactions are recorded and verified on a decentralized ledger secured by cryptography rather than a central authority. While initial participation was highly concentrated in earlier years [Makarov and Schoar, 2021], cryptocurrencies have become widely adopted in recent years.

[2] For additional anecdotes, see the "IMF-FSB synthesis paper: Policies for crypto-assets" from September 2023, or "Bitcoin is a hit in countries facing local currency troubles", published by the Wall Street Journal.

an emerging markets phenomenon.

Households may choose to hold cryptocurrencies for several macroeconomic reasons. Some households may use them to speculate [Auer and Tercero-Lucas, 2022], make illicit transactions [Foley et al., 2019; Alnasaa et al., 2022], or transfer wealth across borders when other methods are inaccessible or prohibitively expensive [von Luckner et al., 2023, 2024].[3] Other households may hold cryptocurrencies to diversify against sovereign risks, such as loss of purchasing power, sovereign default, hyperinflation, government overreach, or policy uncertainty [Yu et al., 2025; Cardozo et al., 2024].

We present new evidence of the macroeconomic drivers of crypto adoption by combining the cross-country crypto mobile app data of Auer et al. [2023] with a comprehensive set of macro-financial variables. We account for cross-country spillovers and employ modern penalized variable selection techniques, which identify prominent roles for several factors, notably sovereign default risk, that have not been emphasized in prior work. To further sharpen our analysis, we implement an event-study that exploits the staggered timing of sovereign credit risk events associated with sovereign CDS jumps across countries. As such, our work builds on a growing literature that exploits cross-country variation to understand the macroeconomic drivers of crypto adoption [Alnasaa et al., 2022; Yu et al., 2025; Auer et al., 2023].

Our findings suggest that sovereign default risk plays an important role in explaining cryptocurrency adoption patterns. Specifically, a 10% increase in sovereign CDS spreads is associated with a 2.8-3.6% increase in the usage and downloads of crypto apps. Crypto

[3]The 2018 Initial Coin Offering (ICO) boom and bust continues to serve as a central example of momentum and speculation driven crypto adoption [Howell et al., 2020; Davydiuk et al., 2023; Chava et al., 2025].

adoption is more responsive to sovereign CDS spreads in emerging economies and when the social cost of default is high (measured as the sum of public debt and bank credit to the non-financial sector, scaled by GDP). These findings are consistent with the pronounced precautionary motives of households in emerging markets, and with increasing household attentiveness to sovereign default risk when the economic cost of sovereign default is high. Additionally, in an event study setting, we find significant and persistent increases in crypto adoption after sovereign credit risk events. These credit risk events map to a variety of underlying sources. Clustering methods illustrate that these events are associated with high inflation, high social cost of default, and high political instability. While households may not monitor CDS spreads directly, they are likely to consider these underlying macro-financial factors in their assessment of sovereign default risk.

Beyond sovereign risk, we identify other macroeconomic factors associated with crypto adoption, including speculation, sovereign credit ratings, real exchange rates, public debt, bank sector development, political instability and corruption, capital mobility, remittances, sovereign CDS spread spillovers from other countries, and inflation spillovers from other countries. In contrast to the literature, we find a tenuous association between inflation and crypto adoption after controlling for other factors. Specifically, we find that the association between inflation and crypto adoption becomes notably stronger when the social cost of default is high.

Our results confirm several findings from prior studies. For example, Auer and Tercero-Lucas [2022] and Kogan et al. [2024] identify strong speculative motives for crypto adoption, while Auer et al. [2023] highlights global factors such as bitcoin prices and global economic policy uncertainty. Additionally, Alnasaa et al. [2022], Yu et al. [2025], and Auer et al.

[2023] show that remittances, bank sector development, economic policy uncertainty, and corruption at the country level are associated with measures of crypto adoption. Several studies, including Alnasaa et al. [2022], Aiello et al. [2023], Auer et al. [2023], Weber et al. [2023], and Cong et al. [2024], emphasize the importance of inflation as a factor. Our analysis builds on these insights by highlighting the critical role of sovereign default risk. We also confirm that inflation, while not consistently a dominant factor, gains significance in macroeconomic environments that are particularly vulnerable to sovereign default.

We construct a cross-country dataset by combining crypto adoption metrics with a comprehensive set of macroeconomic and financial variables from public and non-public sources. The sample period spans August 2015 to June 2022, covering 19 of the G20 countries. Our primary measure of crypto adoption is monthly crypto app downloads, while our secondary metric is the monthly average of daily active crypto app users (MAU). The crypto adoption data is collected by Sensor Tower and made publicly available by the BIS [Auer et al., 2023]. While these mobile app data allow us to conduct cross-country analysis, we note that sophisticated crypto investors may have alternative means of accessing crypto markets. Therefore, it is important to caveat that our results are most likely to speak to the behavior of marginal retail crypto users that rely on crypto exchanges' mobile apps to access crypto markets. For a subsample of countries in our dataset in which the local bitcoin price premium is observed ([von Luckner et al., 2024]), we find a positive correlation between our mobile app metrics and this alternative proxy, consistent with a positive relationship between crypto app usage and local cryptocurrency demand.

We consider 5-year sovereign CDS spreads as our primary measure of sovereign default risk. We also use Moody's sovereign credit ratings data as a complementary sovereign risk

indicator throughout the analysis. In addition, we collect data on a wide range of variables to gauge the importance of different macro factors for crypto adoption. For example, inflation and adoption momentum have been suggested to influence crypto adoption in the academic literature and in public discourse. We also collect data on: exchange rates, interest rates, stock market volatility, capital mobility, public debt, bank sector development, stock market development, political instability, corruption, remittances, informal economy sector, cellular subscriptions, and population. We also construct several distance-weighted variables that allow us to quantify cross-country spillovers (e.g., whether macro-financial conditions of neighboring countries are consequential for crypto adoption).

Our baseline analysis estimates univariate and multivariate regressions of crypto adoption metrics on macro factors. Across specifications, we find that a 10% increase in sovereign CDS spreads is associated with an additional 2.8-3.6% growth in crypto adoption metrics. We estimate panel regressions with country and time fixed effects in order to reduce non-random variation arising from unobserved heterogeneity. We motivate our specification by showing that the majority of variation in crypto adoption metrics can be explained by country and time fixed effects. In other words, crypto adoption patterns across countries and over time are far from random, and this could significantly bias regression estimates if left unaddressed. For example, we show that the negative association between sovereign CDS spreads and crypto adoption metrics turns significant and positive after controlling for fixed effects.

The univariate regression specification models the logged crypto adoption metrics as a function of each macroeconomic variable, with each covariate considered individually. CDS spreads, CPI inflation, real exchange rates, crypto adoption momentum, and sovereign credit ratings are identified as significant correlates of both crypto downloads and MAU. We then

extend the univariate fixed effect regressions to a multivariate regression that includes all of the covariates. The covariate space is quite large, with over 50 covariates when accounting for all of the macroeconomic factors plus each sovereign credit rating category. To refine our multivariate analysis, we apply a cross-validated LASSO variable selection procedure with post-double selection [Belloni et al., 2014]. We find that sovereign CDS spreads survive the selection procedure and remain an economically and statistically significant predictor of crypto adoption. In contrast, the coefficient on CPI inflation diminishes and becomes statistically insignificant. CPI inflation of other countries, however, are significantly associated with a given country's rate of crypto adoption. Crypto adoption momentum, remittances, real interest rates, and corruption are significantly and positively associated with crypto adoption. Exchange rate weakness and underdeveloped banking sectors are also significantly associated with crypto adoption.

We split our sample into Advanced Economies (AEs) and Emerging Market Economies (EMs), and find significant heterogeneity in the relationship between sovereign CDS spreads and crypto adoption. A 10% increase in sovereign CDS spreads associated with an additional 6% growth of crypto downloads in EMs and 2% additional growth in AEs. We discuss how the precautionary motives of EM households may offer an explanation for their high propensity to adopt cryptocurrencies when sovereign default risk is elevated [Heltberg et al., 2015; Badarinza et al., 2019], and when there is need to circumvent capital controls [von Luckner et al., 2023, 2024].

We show that the association between sovereign CDS spreads and crypto adoption is strongest when the social cost of default is high (SCD). We construct a simple measure of the SCD as the sum of public debt and bank credit to the non-financial private sector, divided

by GDP. This measure is inspired by the many studies showing that the macroeconomic costs of sovereign default increase in the size of the public sector and are amplified by the bank sector [Farah-Yacoub et al., 2024; Gennaioli et al., 2014; Hébert and Schreger, 2017; Farah-Yacoub et al., 2024].[4] In EMs, we find that the association of sovereign CDS with crypto downloads is monotonically increasing in SCD quintiles. Within the lowest default cost quintile, a 10% increase in CDS spreads is associated with 2.2% growth in crypto downloads. Within the highest default cost quintile, a 10% increase in CDS spreads is associated with 5.4% growth in crypto downloads. We find a similarly increasing, although non-monotonic, pattern among AEs. Lastly, we find that the sensitivity of crypto downloads to inflation is heterogeneous and increasing in default cost quintiles for both EMs and AEs. In EMs, a 1 percentage point increase in inflation is associated with 1.2% growth of crypto downloads in the lowest default cost quintile, but 11.5% growth of crypto downloads in the highest default cost quintile. These results suggest that the often-noted relationship between inflation and crypto adoption may be rooted in the inflationary consequences of sovereign default.

Our panel data analysis builds on prior work by adding new macro predictors of crypto adoption, and our use of LASSO to reduce dimensionality helps isolate determinants of crypto adoption with economically important and orthogonal variation. Neither of these methods, however, addresses potential sources of endogeneity in the link between sovereign default risk and crypto adoption, nor can it explain why household adoption responds to CDS spreads – a measure households are unlikely to monitor. Furthermore, given the short time span of our panel data, methods that rely primarily on time series variation in sovereign

[4]For evidence of sovereign defaults hampering financial intermediation and credit provision, also see Adelino and Ferreira [2016], Bocola [2016], Andrade and Chhaochharia [2018], Gennaioli et al. [2018], Sosa-Padilla [2018], and Başkaya et al. [2024].

default risk (e.g., VARs or local projections) are not well-suited to our analysis. Instead, we use an event study difference-in-differences design that exploits discrete, country-specific realizations of heightened sovereign default risk.

We estimate event study regressions to trace the dynamics of cryptocurrency adoption around systematically identified credit risk events. Our baseline approach defines a credit risk event as a positive CDS change exceeding the 70th percentile of positive monthly changes in CDS spreads. We identify a total of 205 credit risk events this way. On average, crypto app downloads and usage rise significantly and persistently following these sovereign credit risk events, by 10-15%, suggesting that our panel regression results are robust to relatively strong timing restrictions. These event study estimates are robust to alternative thresholds for identifying events, manually identifying country-specific credit risk events within our sample using media narratives, and when we define credit risk events as sovereign credit rating downgrades.

Although our event study analysis provides stronger evidence of a causal link between sovereign default risk and crypto adoption, it is unlikely that households directly monitor CDS spreads in their assessment of sovereign risk. Moreover, sovereign default risk, and therefore sovereign CDS spreads, are a reflection of various underlying shocks and processes. Therefore, in order to better understand this measured relationship between household crypto adoption and sovereign CDS spreads, we apply an unsupervised cluster analysis of the 205 identified credit risk events on macro-financial variables. These events are clustered in three groups, which we identify as pertaining to high inflation, high SCD, and high political instability, respectively. Fortunately, these are also interpretable underlying factors that are likely to be used by households to assess sovereign risk. When we split our credit

risk events by cluster and analyze our event study regressions for each event type, we find that crypto downloads responds strongest to credit risk events that are accompanied by high inflation and high political instability.

The remainder of the paper is structured as follows. Section 2 provides details on data sources, collection, construction, and preliminary analysis. Section 3 presents the results of univariate and multivariate regressions of crypto adoption metrics on sovereign CDS spreads and other macro factors. Section 4 presents event study evidence of crypto adoption around sovereign default risk events and shows that these events map to instances of high inflation, high social cost of default, and high political instability. Section 5 concludes.

2 Data

Our dataset consists of country-month observations spanning from August 2015 to June 2022 and is compiled from a diverse array of public and nonpublic sources. The dataset aims to capture the key variables most frequently associated with crypto adoption in both the academic literature and public discourse. Table 1 provides summary statistics, while Table 2 offers detailed descriptions of each variable. We obtained a balanced cross-country panel after limited forward-filling which does not materially affect the analysis (see Table 2). The dataset includes 19 countries representing a mix of emerging and advanced economies: Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, Saudi Arabia, South Africa, South Korea, Turkey, the United Kingdom and the United States.

2.1 Crypto adoption metrics and sovereign CDS spreads

The dependent variables of interest are monthly crypto adoption metrics at the country level. Our primary measure is monthly crypto app downloads, and the secondary measure is the monthly average of daily active crypto app users (MAU). The data come from Sensor Tower, a proprietary app intelligence provider, and have been made publicly available by Sensor Tower and the BIS. The coverage of these crypto adoption metrics dictates the time period and countries included in our analysis.

Downloads serve as a proxy for the extensive margin of crypto adoption, as a potential adopter must download an app before purchasing cryptocurrencies. While downloads inform crypto purchases, they are less likely to inform sales because apps need not be deleted to sell crypto. One limitation of using downloads data as our measure of crypto adoption is that it does not reveal actual purchase volumes of cryptocurrencies by app users.

Crypto app downloads and usage are positively correlated within countries, but correlations vary across countries (Figure 1). Usage metrics are counted any time a downloaded crypto app is opened. Therefore, downloads precede usage and we verify this at the aggregate level.[5] Usage statistics are a slightly noisier measure of adoption compared to downloads, because usage may occur after initial adoption of crypto, and usage may entail cryptocurrencies being both bought and sold.

In the context of sovereign risk, one may posit that more individuals download crypto apps when sovereign risk is high. Individuals do not necessarily delete these apps when

[5]We test for Granger Causality using fixed effect panel regressions. 1-month lagged ln(Downloads) significantly predicts contemporaneous ln(MAU) while controlling for 1-month lagged ln(MAU) and country and time fixed effects (Driscoll-Kraay t-statistic of 3.57). However, 1-month lagged ln(MAU) does not significantly predict contemporaneous ln(Downloads) controlling for 1-month lagged ln(Downloads) and country and time fixed effects (Driscoll-Kraay t-statistic of 0.47).

sovereign risk recedes, but fewer individuals may download apps. Because usage statistics do not distinguish between buying or selling crypto, it is conceivable to have high usage both when sovereign risk is high (if individuals buy crypto) and when sovereign risk declines (if individuals sell crypto that they previously bought). Consequently, *a priori* we can expect a stronger relationship between sovereign risk and crypto app downloads than sovereign risk and crypto app usage. This is consistent with the results we document.

The key independent variable of interest is the 5-year sovereign CDS spread. CDS spreads are the primary measures we use to test whether crypto adoption is associated with sovereign default risk. While many studies examine the relationship between inflation and crypto adoption, empirical evidence of a link between sovereign risk and crypto adoption remains limited. Nevertheless, the inflationary scenarios typically tied to crypto adoption often occur in contexts of failing or unstable governments.[6]

We source daily sovereign CDS spreads from IHS Markit and aggregate daily spreads to monthly averages. We selected the 5-year tenor due to its relative liquidity and because it often serves as the benchmark for CDS indices [Hébert and Schreger, 2017]. Sovereign CDS spreads are particularly useful indicators of sovereign risk because they are forward-looking and react to information faster than sovereign credit ratings [Rodríguez et al., 2019]. That said, we also incorporate sovereign credit ratings into our analysis. We show that numerically-coded credit ratings are highly correlated with CDS spreads in Figure 2.

Figure 3 presents the cross-country median values of the sovereign CDS data and crypto adoption metrics over time. The shaded regions represent the interquartile range across

[6]For example, see "Cryptocurrencies: developing countries provide fertile ground", published in the Financial Times; "Crypto adoption in the Middle East will come from unstable nations", published by CoinDesk; and "Cryptocurrencies rise in popularity in the world's conflict zones", published by The Guardian.

countries within each month. The substantial time-series and cross-country variation in these variables is evident. Moreover, a naive examination of these trends suggests a negative relationship between sovereign risk and crypto adoption, as CDS spreads have declined over the sample period while crypto adoption metrics have risen.

However, these observed trends may be driven by unobserved heterogeneity in the data.[7] Table 3 confirms this, reporting R^2 values from regressions of (logged) CDS spreads and crypto adoption metrics on country and time fixed effects (FEs). Together, country and time FEs account for roughly 90% of the variation in these variables. Country FEs explain 86% of the variation in CDS spread levels, while approximately 40% and 50% of the variation in crypto adoption metrics are explained by country and time FEs, respectively. Moreover, panel unit root tests reject the null hypothesis that the key variables contain unit roots after controlling for fixed effects. Figure 4 shows that once these FEs are accounted for, a strong positive relationship emerges between sovereign CDS spreads and crypto adoption metrics. These results underscore the importance of including both time and country FEs in cross-country panel analyses of crypto adoption.

2.2 Crypto adoption metrics and cryptocurrency demand

Figure 5 plots binned means of logged CDS spreads and crypto adoption metrics, after removing country and time fixed effects, against the local bitcoin price premium [von Luckner et al., 2024]. The bitcoin price premium is measured as the log-difference between a country's

[7] Country-specific characteristics, which are difficult to measure, may explain persistent cross-country differences in both CDS spreads and crypto adoption metrics. Simultaneously, global common shocks can induce significant co-variation across countries in a given month. Sovereign credit risk has been linked to both global common factors and country-specific factors [Longstaff et al., 2011; Augustin et al., 2022]. Similarly, crypto adoption metrics across countries appear strongly associated with common factors, such as the global price of bitcoin [Auer et al., 2023].

USD exchange rate implied by bitcoin prices on exchanges and the country's official exchange rate. Our use of the bitcoin price premium data is limited because it is only available for a subset of countries and starts in 2019. It measures country-specific cryptocurrency price pressures and the cost to convert local currency to dollars using cryptocurrencies (e.g., to circumvent capital controls). For this subset of our data, Figure 5 shows that high levels of crypto app downloads and usage are associated with high bitcoin price premia, consistent with our crypto adoption metrics measuring local demand for crypto.[8]

2.3 Additional variables

We include a range of additional variables in our analysis. While CDS spreads are forward-looking, we also collect Moody's sovereign credit ratings as a lagged measure of sovereign default risk. These ratings are categorical and combine both the credit rating and the outlook, e.g., "AAA-negative." Crypto momentum and network effects (e.g., 'speculation') are likely drivers of crypto adoption [Auer and Tercero-Lucas, 2022; Auer et al., 2023]. For instance, speculative motives are often considered key factors behind crypto adoption in many advanced economies and parts of Asia.[9] To capture these momentum and network effects, we include lagged cumulative downloads as a variable.[10]

We consider year-over-year CPI inflation, as inflation risk has been cited as a driver of

[8]Countries with bitcoin price premium data: Argentina, Australia, Brazil, Canada, India, Indonesia, Japan, Mexico, South Africa, UK, US.

[9]See "Cryptocurrency regulation diverges across Asia", published by the Economist Intelligence Unit.

[10]Auer et al. [2023] considers using the global price of bitcoin as a proxy for momentum effects. However, this approach has two limitations. First, the global bitcoin price has no cross-country variation and is collinear with time fixed effects in panel regressions, meaning both cannot be included in regressions simultaneously. As a result, it is difficult to precisely identify the momentum effect from other global factors. Second, momentum effects may vary across countries, which country-invariant variables cannot capture.

crypto adoption in both academic debates and public discourse.[11] Additionally, we include several financial variables that may influence the rate of crypto adoption in an economy: the real exchange rate and its volatility, the real interest rate[12], and stock market volatility. The exchange rate may have a similar effect on crypto adoption as inflation, as a weak exchange rate can similarly raise concerns about the preservation of local purchasing power. Meanwhile, real interest rates and stock market volatility offer measures of prevailing risk appetite and expected returns on traditional financial assets.

We also include several macro-financial factors: international capital mobility, bank sector credit to the non-financial sector, bank sector concentration, public debt, and stock market capitalization. Capital mobility is measured using the Chinn and Ito [2006] financial openness index. Crypto has been shown to act as a vehicle for capital flight [von Luckner et al., 2023, 2024]. Public debt to GDP is a commonly referenced and publicly discussed measure of sovereign risk and debt sustainability. Bank sector credit and concentration serve as indicators of banking sector development [Alnasaa et al., 2022; Auer et al., 2023]. These banking variables are relevant for crypto adoption insofar as (i) crypto offers an alternative financial service to the underbanked[13], and (ii) bank sector vulnerabilities interact with sovereign risk.[14] Stock market capitalization is included as an additional indicator of overall financial development, complementing the bank sector indicators.

Additionally, we consider several macroeconomic factors: population, political instability,

[11] See Alnasaa et al. [2022], Auer et al. [2023], and Liu and Valcarcel [2024] for aggregate evidence, and Aiello et al. [2023], Weber et al. [2023], and Cong et al. [2024] for survey-based evidence.

[12] The real interest rate is calculated as the central bank policy rate minus the inflation rate.

[13] Also see Federal Reserve Board of Governors, "Economic well-being of U.S. households in 2023" (May 2023) and "Debunking the narratives about cryptocurrency and financial inclusion", published by the Brookings Institution.

[14] See Adelino and Ferreira [2016], Bocola [2016], Andrade and Chhaochharia [2018], Gennaioli et al. [2018], Sosa-Padilla [2018].

corruption, cellular subscriptions, informal economy size, and remittances. Population is included to control for mechanical "denominator" effects in our crypto adoption metrics, which are normalized by population. Political instability and corruption, like sovereign and inflation risk, have been proposed as an explanation for crypto adoption [Alnasaa et al., 2022]. We use cellular subscriptions and the estimated size of the informal economy from Kose et al. [2021] as proxies for access to technology and information necessary for downloading and using crypto apps. We also include remittance inflows as a percentage of GDP, since crypto is often debated as an innovation that simplifies remittances and reduces their costs [Rühmann et al., 2020; Auer et al., 2023].[15]

2.4 Variables that allow for cross-country spillovers

We also consider the possibility of cross-country or global spillovers, where variables in one country may affect crypto adoption in another country. To account for this, we construct distance-weighted averages for a select set of variables discussed above.

The distance-weighted variables are constructed using an inverse-distance bilateral weighting scheme. For example, for country i, we consider the distance-weighted average CDS spread of the other countries in the sample ($j \neq i$), with weights w_{ij} corresponding to the inverse of the bilateral distance between countries i and j:

$$X_{-it} = \sum_{j \neq i} w_{ij} X_{jt},$$

where $w_{ij} = \frac{D^{-1}{}_{ij}}{\sum_j D^{-1}{}_{ij}}$ for $i \neq j$, $w_{ii} = 0$, and D_{ij}^{-1} is the inverse of the geographical distance

[15] El Salvador serves as a case study. The country, which frequently receives remittance inflows exceeding 20% of GDP, adopted bitcoin as legal tender in 2021.

between countries i and j. The variable X_{-it} represents the distance-weighted average of X_{jt}, excluding country i, with greater weight given to countries closer to country i. Incorporating variables like X_{-it} allows for the possibility of factors outside country i to influence crypto adoption in country i. In the example using CDS spreads, this approach allows both the CDS spread of country i to impact crypto adoption in country i, and the CDS spreads of other countries $(-i)$ to also influence crypto adoption in country i. We construct distance-weighted averages for six variables: CDS spreads, CPI inflation, real interest rates, capital mobility, stock market volatility, and public debt.

3 Regression Analysis

In this section we present estimates from univariate and multivariate regressions of crypto adoption metrics on sovereign CDS spreads and a broad set of other macroeconomic covariates.

3.1 Univariate regression

We begin by estimating univariate regressions of the crypto adoption metrics on each of the covariates in our data set, one at a time. Throughout the analysis, we consider log-transformed dependent variables, i.e. ln(Downloads) and ln(MAU).[16] We also log-transform several of the covariates. The set of logged covariates are: ln(CDS), ln(Exchange Rate), ln(Exchange Rate Volatility), ln(Stock Market Volatility), ln(Population), ln(CDS, $-i$), ln(Stock Market Volatility, $-i$), and ln(Cum. Downloads, $t-1$), where the latter covariate

[16] As mentioned in the previous section, Table 3 reports that panel unit root tests reject the null hypothesis that the key variables contain unit roots after controlling for fixed effects.

is the log of cumulative downloads, one-month lagged. Covariates indexed by $-i$ correspond to the distance-weighted averages of countries excluding country i. The rest of the variables enter the regressions without any transformation: CPI year-over-year inflation, Real Interest Rate, Public Debt/GDP, Bank Credit/GDP, Bank Sector Concentration, Stock Market Cap/GDP, Political Instability, Corruption, Capital Mobility, Cellular Subscriptions, Informal Economy Size, Remittances/GDP, CPI $(-i)$, Real Interest Rate $(-i)$, Capital Mobility $(-i)$, and Public Debt/GDP $(-i)$. Moody's credit ratings enter as fixed effects.

Univariate regressions are specified as:

$$y_{it} = \alpha_i + \delta_t + \beta X_{it} + e_{it}, \tag{1}$$

where y_{it} is the dependent variable, either ln(Downloads) or ln(MAU), α_i and d_t are country and time (year-month) fixed effects, and X_{it} is one of the covariates. We apply Driscoll-Kraay standard errors which account for general forms of heteroskedasticity, autocorrelation, and cross-sectional dependence in the error term [Driscoll and Kraay, 1998]. We report estimates for β across the univariate regressions of ln(Downloads) in Tables 4 and 5. Several variables exhibit significant correlations with ln(Downloads). Notably, lagged ln(Cum. Downloads) explains roughly 34.6% of the variation in ln(Downloads), given by the within R^2, suggesting strong momentum and network effects in crypto downloads. Meanwhile, Moody's credit rating FEs explain about 30.5% of the variation in ln(Downloads). Note that lagged downloads capture much of the serial correlation in crypto adoption data, while credit rating fixed effects span several categories. Consequently, the high R^2 values for these variables are not unexpected.

Covariates such as ln(Exchange Rate), ln(CDS), and CPI exhibit substantially large within R^2 statistics. We compare the within R^2 across covariates in Figure 6. If we exclude lagged downloads and credit ratings FEs from the rankings, ln(CDS) ranks third in the ln(Downloads) regressions and fifth in the ln(MAU) regressions. The coefficients on ln(CDS) and CPI of 0.367 and 0.036, respectively, are notable.[17] The coefficients suggest that crypto downloads increase by roughly 3.6% when CDS spreads increase by 10% or when CPI inflation increases by 1 percentage point. Crypto downloads also tend to grow by about 2.58% per every 1% depreciation in the real exchange rate. Tables 6 and 7 report univariate estimates for ln(MAU) regressions, showing results that are mostly aligned with those from the ln(Downloads) regressions.

The next section moves to a multivariate regression analysis. While the univariate analysis provides a useful baseline, several of these variables are likely correlated with one another, and with sovereign credit risk. For example, credit ratings, CDS spreads, inflation, exchange rates, interest rates, and public debt all likely inform the propensity of sovereign default (and the crypto adoption associated with it). Our multivariate extensions allow us to better identify the most robust predictors of crypto adoption.

3.2 Multivariate regression and variable selection

In this section we estimate a fully specified regression model of logged crypto adoption metrics on the covariate set described in Section 3.1. The regressions take the following form:

[17] The univariate coefficient estimate of 0.036 on inflation is similar to the 0.037 reported coefficient from the specification of Auer et al. [2023].

$$y_{it} = \alpha_i + \delta_t + \beta_0 \ln(CDS_{it}) + \sum_{p=1}^{P} \beta_p X_{itp} + e_{it}, \tag{2}$$

where (2) closely resembles (1) except that the right-hand side of the regression now includes country and time FEs, logged sovereign CDS spreads $\ln(CDS_{it})$, and all remaining covariates in the vectors X_{itp}.

The covariate space is rather large and correlated, with over 50 variables when considering all covariates plus each Moody's credit rating category individually. Therefore, along with presenting estimates for the fully specified regression, we apply penalized variable selection to identify the most robust drivers of crypto adoption. We apply a LASSO variable selection procedure with cross-validation and post-double selection modified for panel data with fixed effects [Tibshirani, 1996; Belloni et al., 2014].[18] Cross-validated LASSO selects variables by shrinking coefficients toward zero through the L1 penalty function, while post-double selection allows for appropriate inference on OLS regressions estimated using the selected set of covariates with non-zero LASSO coefficients.

We estimate (2) in four steps. First, we regress all variables, dependent and independent, on country and time FEs and store the residuals. In the second step, we apply 10-fold cross-validated LASSO on the regression specification shown in (2), but using the residuals of the variables from the first step in place of y_{it} and without FEs α_i and δ_t which were estimated in the first step. We also impose in the LASSO that the Moody's credit rating FEs are not penalized. As a result, country, time, and credit rating FEs are implicitly estimated and remain present throughout the variable selection procedure. In the third

[18] Out-of-sample prediction under cross-validation with FEs is problematic because some countries and time periods in the training set may be absent from the validation sets, and *vice versa*.

step, we apply double selection by estimating another cross-validated LASSO, this time regressing the residuals of $\ln(CDS_{it})$ on the residuals of the other covariates. Under post-double selection, the union of variables with non-zero coefficients from the two LASSO regressions is identified as the selected set of variables. Finally, we take only the union of variables with non-zero coefficients and estimate another version of (2) via OLS.

Table 8 reports the results. For the ln(Downloads) regression, the variable selection procedure drops three variables.[19] For the ln(MAU) regression, the variable selection procedure drops six variables.[20] While Table 8 offers several results, a few notable patterns emerge related to the role of sovereign risk. First, sovereign CDS spreads survive the selection procedure and remain robust and statistically significant predictors of crypto adoption metrics even after controlling for credit ratings FEs and other covariates. This suggests that the sensitivity of crypto adoption to sovereign CDS spreads reflects more than just the effect of persistent credit risk information embedded in credit ratings. Persistent factors related to credit risk are largely accounted for by credit ratings FEs and other macroeconomic controls. Meanwhile, CDS spreads also incorporate new and forward-looking information that most of these variables do not [Rodríguez et al., 2019]. To benchmark the economic magnitude of this effect, we translate the elasticity into changes in the number of crypto app downloads. In the LASSO-selected specification in Table 8, the coefficient on ln(CDS) is approximately 0.36. A 10 percent increase in sovereign CDS spreads is therefore associated with approximately a 3.6 percent increase in monthly crypto app downloads. Evaluated at the sample mean of 214 downloads per 100,000 inhabitants (Table 1), this corresponds to about 7–8 additional

[19] The three dropped variables are: ln(Exchange Rate Volatility) ln(Stock Market Volatility, $-i$), and Public Debt/GDP ($-i$).

[20] The six dropped variables are: ln(Exchange Rate Volatility), Public Debt/GDP, Stock Market Cap/GDP, Remittances/GDP, Real Interest Rate ($-i$), Public Debt/GDP ($-i$).

downloads per 100,000 inhabitants in that month. For a country with a population of 50 million, this implies roughly 3,700 incremental crypto app downloads in response to a 10 percent rise in CDS spreads.

Other factors also appear robustly associated with crypto adoption. Most importantly, lagged cumulative downloads continues to be a powerful predictor of both crypto adoption metrics, suggesting a strong role for momentum and speculation consistent with Auer and Tercero-Lucas [2022] and Auer et al. [2023]. Countries receiving more remittances also download and use crypto apps at higher rates. Both more concentrated and more developed bank sectors are associated with fewer crypto app downloads, suggesting that access to financial services plays an important role for crypto adoption. High real interest rates and weak exchange rates are associated with more crypto app downloads. A greater degree of corruption is positively associated with crypto app downloads and usage, consistent with Alnasaa et al. [2022]. Finally, CPI inflation is statistically insignificant in all regressions, but CPI inflation rates *of other countries* are significantly associated with the crypto adoption metrics of country i.

3.3 Heterogeneity across advanced and emerging economies

This section tests for heterogeneity in the relationship between sovereign CDS spreads and crypto adoption. We begin by splitting the sample into emerging market economies (EMs) and advanced economies (AEs) based on IMF classifications. This stratification is natural given the distinct economic characteristics of these two groups. EMs and AEs may also exhibit differences in their motives for adopting crypto. For instance, it would not be surprising

to find that sovereign default risk is a stronger predictor of crypto downloads in EMs, where sovereign default and government instability risks are more prevalent.

Table 9 reports estimates from the multivariate regression specification shown in (2), with the sample split into EMs and AEs. For conciseness, we report results on crypto downloads throughout this section. The sensitivity of crypto downloads to CDS spreads is evident in both EMs and AEs, but the effect is three times larger in EMs. A 10% increase in the sovereign CDS spread is associated with 6% additional growth in crypto downloads in EMs and roughly 2% additional growth in AEs. Table 9 also shows that weak exchange rates and high public debt significantly predict more crypto downloads in EMs but not in AEs. Meanwhile, lagged cumulative downloads, bank sector size, remittances, and corruption are significant predictors of crypto downloads in both EMs and AEs. Interestingly, high local stock market volatility is associated with fewer crypto downloads in EMs but more crypto downloads in AEs. One explanation may be that in EMs, high local stock volatility coincides with economic stress that limits overall risk-taking. While in AEs, increased crypto adoption amid high stock volatility might represent some degree of substitution between high-volatility assets.

The precautionary motives of EM households might explain their propensity to turn to crypto when sovereign default risk is elevated. EM households face particularly high risks from economic volatility, government instability, and asset loss [Heltberg et al., 2015]. This increases the importance of social insurance as a risk mitigation tool. However, the support infrastructure provided by EM governments is often inadequate, especially under sovereign default [Kahn, 2005]. As a result, household portfolio decisions may be influenced by the precautionary need to self-insure against macroeconomic risks (e.g., a sovereign default

that induces significant asset losses and hyperinflation). Consistent with this, unlike their peers in advanced economies, EM households tend to hold much of their wealth in tangible assets such as real estate, gold, or large US banknotes, and relatively low levels of financial assets [Badarinza et al., 2019].[21] Cryptocurrencies may be viewed similarly to these tangible assets, as they can be default-immune and self-custodied. However, unlike tangible assets, cryptocurrencies also provide a vehicle for capital flight [von Luckner et al., 2023, 2024]. And importantly, they may hedge household portfolios against country-specific macroeconomic or political risks [Murakami and Viswanath-Natraj, 2022; Cong et al., 2024].

3.4 Effect heterogeneity and the social cost of default

Motivated by the literature on the social and economic costs of sovereign default, we hypothesize that the association between sovereign CDS spreads and crypto adoption might be non-linear, strengthening as the social cost of sovereign default (SCD) increases. The sovereign default literature identifies the size of the domestic banking system, in addition to the public sector, as indicators of the potential SCD.[22] The social costs of sovereign default are numerous, including large output losses, rising poverty rates, and the collapse of public goods and associated social safety nets [Farah-Yacoub et al., 2024]. Sovereign default also has large financial effects by impairing the valuation of public debt and adversely impacting bondholders through wealth effects. The SCD is further amplified through banks, which are often the largest domestic holders of sovereign bonds. Lower debt valuations negatively affect

[21] This holds even at the very top of the wealth distribution in EMs. Note that we considered controlling for gold demand, however, cross-country data coverage for gold demand does not sufficiently overlap with our panel of countries [Starr and Tran, 2008]. We also attempted to collect data on country-level holdings of U.S. physical banknotes, but such data is unavailable, with only aggregate estimates of foreign demand for U.S. banknotes available [Judson, 2024].

[22] See, for example, Hilscher and Nosbusch [2010] and Gerlach et al. [2010].

bank balance sheets and increase solvency risk [Acharya et al., 2014; Gennaioli et al., 2014; Hébert and Schreger, 2017]. A large body of evidence links these solvency risks associated with sovereign default to hampered financial intermediation and credit provision [Adelino and Ferreira, 2016; Bocola, 2016; Andrade and Chhaochharia, 2018; Gennaioli et al., 2018; Sosa-Padilla, 2018; Başkaya et al., 2024].

Our test constructs a simple measure of SCD by computing the sum of public debt and bank credit to the non-financial sector, divided by GDP. The variable is then sorted into quintiles. We estimate the following regression specification:

$$y_{it} = \alpha_i + \delta_t + \sum_{k=1}^{5} \beta_k \ln(CDS_{it}) \times \mathbf{1}_{itk}^{SCD} + e_{it}, \tag{3}$$

where $\mathbf{1}_{itk}^{SCD}$ is an indicator equal to 1 when the SCD of country i at time t falls into quintile k, and 0 otherwise. The dependent variable y_{it} is ln(Downloads), and we estimate these regressions for EMs and AEs separately. This allows us to test whether the effect of sovereign CDS on crypto adoption strengthens under higher SCD.

Results are reported in Figure 7. In EMs, the sensitivity of crypto downloads to CDS spreads, given by the estimates of β_k, increases monotonically across SCD quintiles. Within the lowest SCD quintile, a 10% increase in CDS spreads is associated with 2.2% growth in crypto downloads. However, within the highest SCD quintile, the same 10% increase in CDS spreads is associated with 5.4% growth in crypto downloads. The sensitivity of crypto downloads to CDS spreads also increases with SCD among AEs, but the coefficients are much smaller and even negative within most quintiles.

3.5 Inflation, crypto adoption, and the social cost of default

Cryptocurrency adoption has been linked to inflation risks in both AEs and EMs [Alnasaa et al., 2022; Auer et al., 2023; Aiello et al., 2023; Weber et al., 2023; Cong et al., 2024]. In univariate regressions, we also find a large and significant response of crypto downloads to CPI inflation rates (Table 4). However, after including controls and splitting between EMs and AEs, we observe a substantially weaker relationship, with the coefficient on inflation shrinking substantially and becoming statistically insignificant (Tables 8 and 9). These results suggest that inflation's influence on crypto adoption may be heterogeneous, non-linear, or reflecting other correlated macro conditions. For instance, the underlying shocks driving inflation dynamics may not all incentivize crypto adoption in the same way (e.g., inflation from monetary or fiscal risks versus inflation caused by excess demand or supply constraints). To test whether default risk helps explain inflation's heterogeneous effect on crypto adoption, we re-estimate (3), replacing ln(CDS) with CPI inflation. We then examine how the sensitivity of crypto downloads to inflation varies with our measure of SCD.

Figure 8 reports the results. The effect of inflation on crypto downloads is indeed heterogeneous in both EMs and AEs. In EMs, the effect of inflation on crypto adoption increases monotonically across SCD quintiles. In the lowest default cost quintile, crypto downloads in EMs increase by 1.2% for every 1 percentage point of inflation. However, within the highest SCD quintile, the effect estimate increases nearly 10-fold: crypto downloads in EMs increase by 11.5% for every 1 percentage point of inflation. Inflation is also associated with higher rates of crypto downloads in AEs when the SCD is greater, although the relationship is not monotonic. For instance, AEs in the lowest SCD quintile see a 0.6% increase in crypto

downloads for every 1 percentage point of inflation, while crypto downloads increase by 8.4%, 9.1%, and 3.4% for every 1 percentage point of inflation in the third, fourth, and fifth SCD quintiles, respectively. These results suggest that SCD may be an important underlying factor explaining the often-noted inflation motive for crypto adoption. Taken together, these results indicate that inflation might not causally explain crypto adoption; instead, inflation matters in the context of default risk.

4 Crypto Adoption around Credit Risk Events

Thus far, our regression evidence relies heavily on cross-sectional variation. In this section, we examine how credit risk events, defined as large changes in CDS spreads, drive crypto adoption not just in the cross-section but over time. We consider several approaches, but as a baseline, our methodology classifies credit risk events as positive monthly changes in CDS spreads exceeding the 70th percentile of the subset of *positive* CDS changes in our dataset. This approach to tracking sovereign default risk is consistent with those used by practitioners. For example, the Council on Foreign Relations' Sovereign Risk Tracker[23] uses sovereign CDS as a measure of a country's level of default risk. The rationale for using a market-based measure of sovereign default risk based on sovereign CDS is that events identified based on jumps in these spreads are (i) related to perceptions of sovereign credit risk of market participants, including sophisticated investors, and (ii) unlikely to be anticipated. The lack of anticipation is due to the ability of investors with advance information or more timely belief-updating to trade and incorporate their information into prices, which would lead to

[23] https://www.cfr.org/tracker/cfr-sovereign-risk-tracker

price drift before anticipated events.

We test the effect of these credit risk events on crypto adoption by specifying event study regressions of the following form:

$$y_{it} = \alpha_i + \delta_t + \sum_{h \in [-8,8]} \phi_h \mathbf{1}_{i,t+h}^{event} + \beta \ln(\text{Cum. Downloads}_{i,t-1}) + e_{it}, \tag{4}$$

where the outcome variable is either logged downloads or MAU, and the indicator, $\mathbf{1}_{i,t+h}^{event}$, equals 1 in country-year-months where a credit risk event occurs and 0 otherwise. Eight months of leads and lags of the indicator variable enter the regression, and estimates of ϕ_h summarize the impact of the event on crypto adoption metrics h months before or after the event, where $h \in [-8, 8]$. Cumulative crypto app downloads is included in the regressions to control for persistent momentum effects. We also include fixed effects.

The 70th percentile of positive CDS changes is equal to a monthly increase in CDS spreads of about 8.94 basis points. 205 observations across 16 countries are identified as credit risk events. For robustness, we also consider the 90th percentile of (uncensored) CDS changes, and we additionally consider an approach where we manually identify plausibly exogenous credit risk events using media narratives.

Figure 9 reports the results as the percent impact of credit risk events on the outcome variable. The figures report coefficient estimates of ϕ_h (multiplied by 100) for each month, up to 8 months before and after the month of the credit risk event, along with 90% Driscoll-Kraay confidence bands. The left-panel traces the average effect of credit risk events on crypto downloads. Crypto app downloads increase by roughly 15% in the months following a credit risk event, and the effect is persistent. The right-panel traces the average effect

of credit risk events on MAU. Crypto app usage increases significantly in the month of the credit risk event, and continues to rise in the months after the event. The event-study magnitudes are also economically meaningful when translated into number of downloads. The estimates in Figure 8 imply that downloads rise by about 10–15 percent in the months after a credit risk event. Using the sample mean of 214 monthly downloads per 100,000 inhabitants (Table 1), this corresponds to roughly 21–32 additional downloads per 100,000 inhabitants per month following an event. For a country with a population of 50 million, this amounts to approximately 10,500–16,000 extra crypto app downloads per month while the effect persists, consistent with the persistence documented in Figures 8–10.

4.1 Robustness

As a first robustness check, Figure 10 reports the event study results using the 90th unconditional percentile of CDS changes as the threshold for classifying credit risk events. This approach does not consider skewness in the distribution of sovereign CDS changes, and so has less power. Nevertheless, estimates presented in Figure 10 are consistent in sign and magnitude with our preferred event study analysis.

As a second robustness check, we take an alternative approach in which we manually identify sovereign credit risk events associated with both large positive CDS changes and associated with media coverage. As in our main set of events based on sovereign CDS jumps, the timing of these events is precisely identified. Because they were widely publicized, we can also identify media narratives associated with each event. We start by identifying notable risk events across the country sample based on positive CDS changes. We identified 52 events in

total. However, many of the identified events exhibit common timing across several countries associated with the COVID-19 pandemic or US monetary policy. We exclude these common events and focus on 25 idiosyncratic, country-level events reported in Table 10.[24] These events are linked to a variety of news and are distributed evenly across our 2015-2022 sample period. The events can be mapped to news about sovereign default, political uncertainty, high inflation, economic deterioration, natural disasters, or risk of military conflict.

We present event study estimates using these manually identified credit risk events in Figure 11. Consistent with the systematic approach of identifying credit risk events based on sovereign CDS jumps, crypto adoption metrics increase notably around and following credit risk events linked to media coverage and narratives, and have a relatively more persistent impact on crypto downloads than MAU.

As an additional robustness check, we examine how crypto downloads and usage changed around Moody's sovereign credit rating downgrades within our sample period. We view downgrades as a supplemental measure of credit risk events to test the robustness of our main event study design. We identify 20 sovereign credit downgrades during our sample period, and we report these in Table 11. We replace events identified by jumps in sovereign CDS spreads or a narrative approach with events based on sovereign credit rating downgrades occurring within a country-month observation. Figure 12 reports the results, showing that crypto adoption also increases significantly around sovereign downgrade events, although the effects are not persistent. Given prior work on the timeliness of credit ratings (e.g., Bruno et al. [2016]) and decrease in statistical power in this sample of events, less precision in

[24] Common shocks in CDS spreads across countries may reflect non-sovereign default risks such as changes in global financial conditions or risk premia [Longstaff et al., 2011].

estimates in this robustness test should be expected.

4.2 Credit risk event classification

It is unlikely that households monitor sovereign CDS spreads to assess sovereign risks. And sovereign risk is not exogenous itself but rather a manifestation of other shocks and processes. Therefore in this section, we try to better understand the fundamental factors underlying these credit risk events that are more likely to enter the households' assessment of sovereign risks. In consideration of this, we apply a simple clustering analysis. We take our 205 credit risk events identified as exceeding the 70th percentile of positive CDS changes and cluster them on a set of macro-financial variables: CPI, the exchange rate, public debt/GDP, bank credit/GDP, political instability, stock market volatility, and capital mobility.

We use a standard unsupervised, unscaled k-means clustering algorithm with $k = 3$ groups. To fix the result of the clustering algorithm which selects starting points randomly, we allow for 25 random initial centroids and select the one with the lowest total within-cluster sum of squares. Table 12 reports the results. The three clusters of credit risk events appear to map to three different fundamental macro-financial themes. Credit risk events in cluster 1 appear associated with double-digit inflation (average within-cluster inflation of 45%). Credit risk events in cluster 2 appear associated with high SCD, as this cluster corresponds to events characterized by the largest average values for both public debt/GDP and bank credit/GDP. Credit risk events in cluster 3 appear associated with high political instability. Clusters 1, 2, and 3 have 39, 30, and 136 credit risk event observations, respectively.

Finally, we split the sample of credit risk events by these three clusters and separately

estimate event study regressions (4) for each subset of events.[25] Figure 13 reports the results. We find that the response of crypto downloads around credit risk events is most pronounced among events of clusters 1 and 3, i.e., credit risk events associated with high inflation and high political instability. Crypto downloads following credit risk events in cluster 2 (high SCD) appear to marginally increase following the event, but the estimates are measured imprecisely and are not statistically significant.

5 Concluding Remarks

In this paper, we investigate the macroeconomic factors driving cryptocurrency adoption across countries, with a particular focus on sovereign default risk. By constructing a cross-country dataset that combines crypto adoption metrics with a comprehensive set of macroeconomic and financial variables, we present robust evidence that sovereign default risk is significantly associated with cryptocurrency adoption across countries and over time. Our baseline finding is that a 10% increase in sovereign CDS spreads is associated with a 2.8-3.6% increase in crypto app downloads and usage. This relationship is stronger in emerging market economies (EMs) compared to advanced economies (AEs), and when the social cost of default is higher.

Crypto adoption also increases significantly after large credit risk events, suggesting that the relationship holds under relatively strong timing restrictions. To understand why households respond to sovereign CDS spreads when it is unlikely that they monitor them, we map these credit risk events to specific fundamental conditions and find that they are associated

[25]For each of the three cluster-specific event study regression, we exclude from the non-treated set the observations that fall into the other two clusters.

with factors that households are likely to take into their assessment of soveriegn risk, such as high inflation, debt levels, and political instability.

These insights have important implications for practitioners, policymakers and regulators. As cryptocurrencies continue to gain traction, understanding crypto investors' demand patterns in response to sovereign risk can help authorities design more effective financial stability policies. For example, the adoption of cryptocurrencies might amplify the effects of sovereign risk on financial intermediation. Sovereign risk lowers the valuations of sovereign assets held by banks, whereas an ensuing flight to crypto out of bank deposits could simultaneously raise the volatility of bank liabilities over the short run. Further research could explore the long-term implications of this phenomenon, including the role of cryptocurrencies in financial (dis)intermediation, and how they mitigate or exacerbate financial stability.

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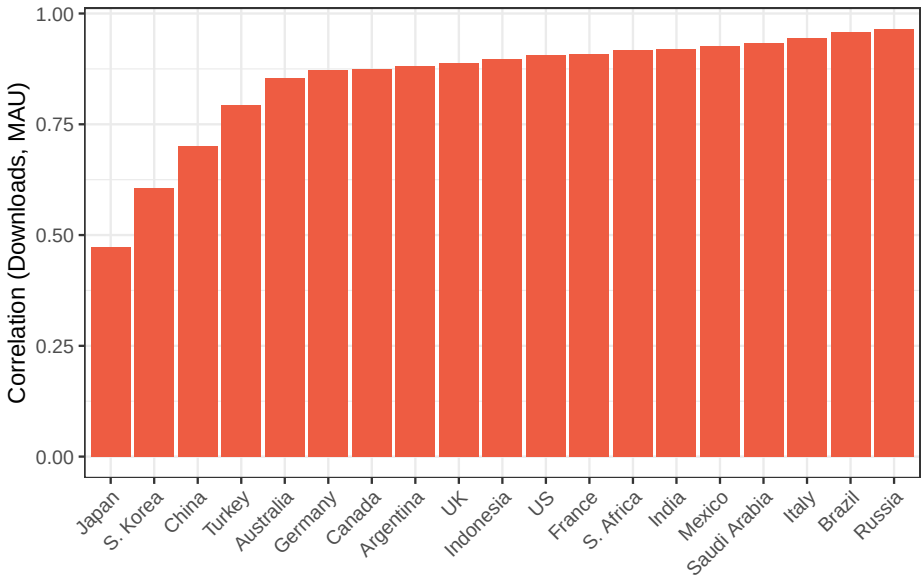
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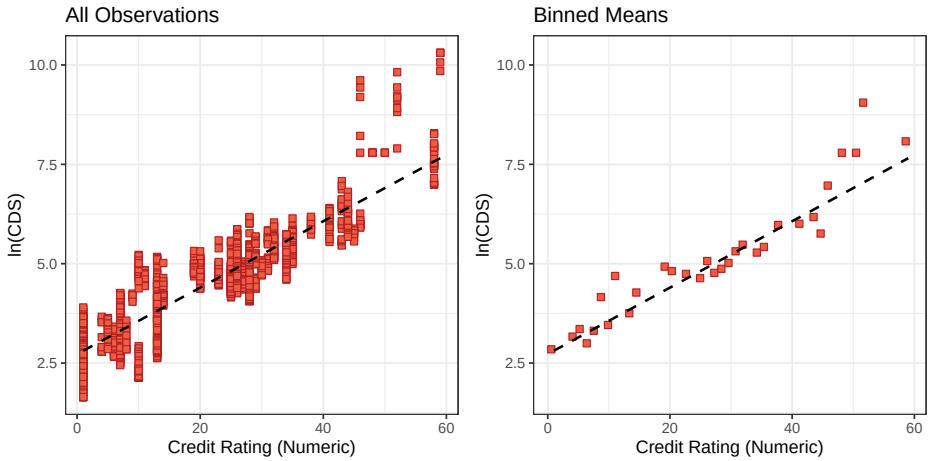
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Figure 1: Correlations of Downloads and MAU by Country



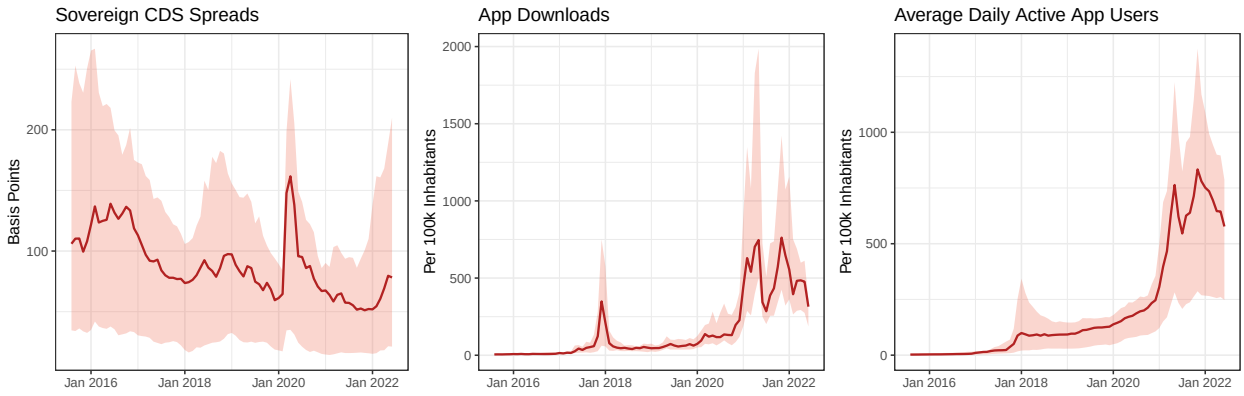
Sample correlation coefficients between Downloads and MAU by country.

Figure 2: Scatterplots of Numeric Moody's Sovereign Credit Ratings and CDS Spreads



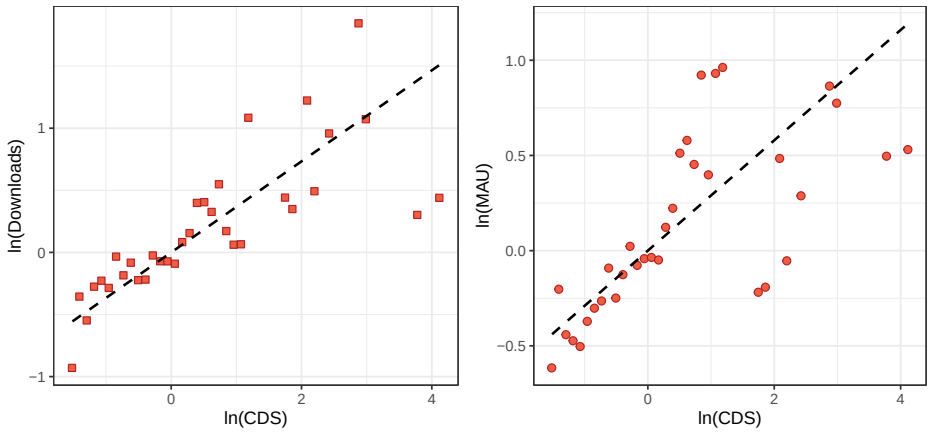
Each point in the right-panel corresponds to the binned mean, where each bin contains 50 observations. The dashed line is the OLS slope estimate. Categorical sovereign credit ratings are coded numerically based on rating-outlook pairs, starting with a value of 1 for "AAA-stable" and then increasing by 1 sequentially with lower rating-outlook pairs.

Figure 3: Sovereign CDS spreads and Crypto Adoption Metrics



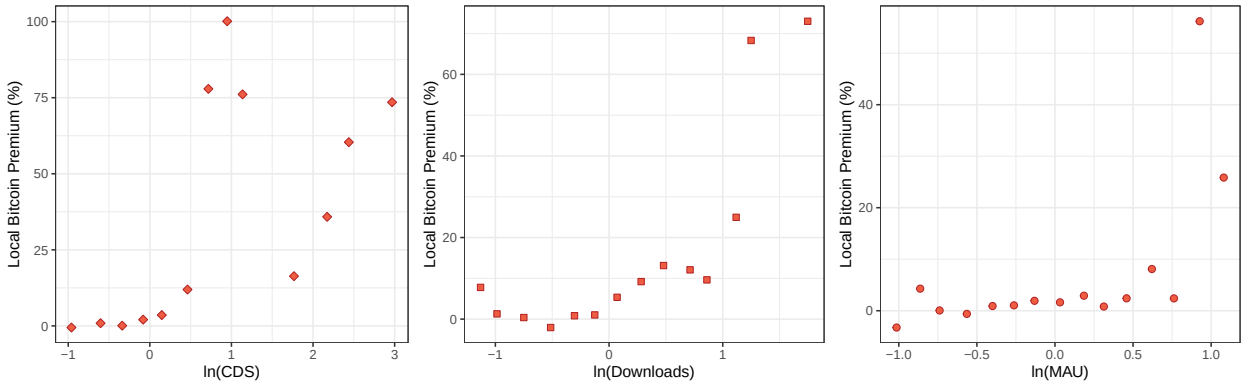
The lines indicate median values calculated across countries within each period. Shaded region indicates the inter-quartile range.

Figure 4: Binned Scatterplots of CDS Spreads and Crypto Adoption Metrics after Removing Fixed Effects



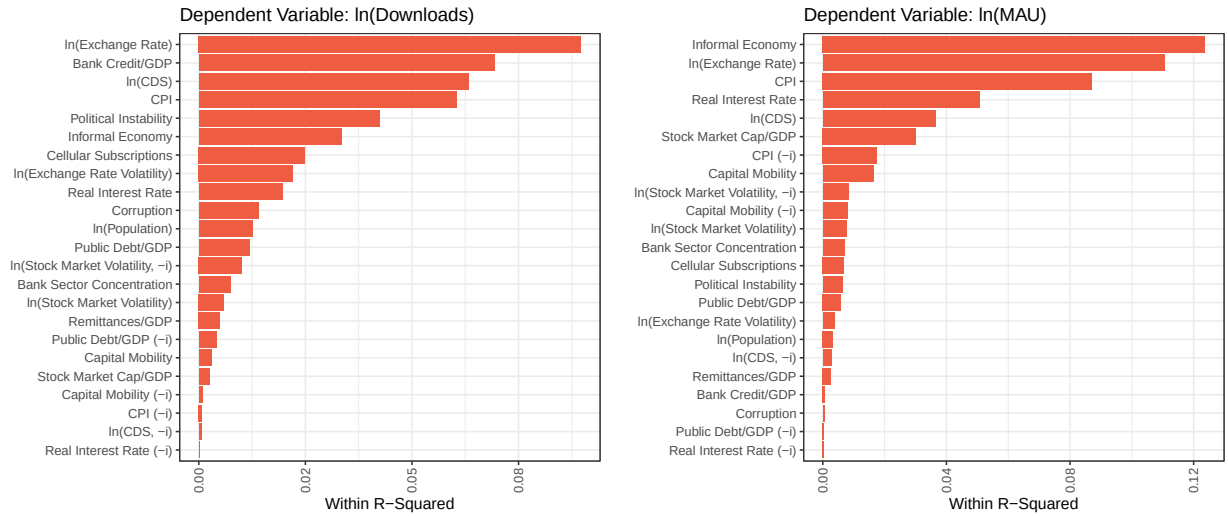
Each point corresponds to the binned mean. The dashed line is the OLS slope estimate. Fixed effects are removed from the variables by estimating regressions of ln(CDS), ln(Downloads), ln(MAU) on country and time fixed effects, respectively. The residuals from these regressions are plotted.

Figure 5: Binned Scatterplots of CDS Spreads and Crypto Adoption Metrics against the Local Bitcoin Premium



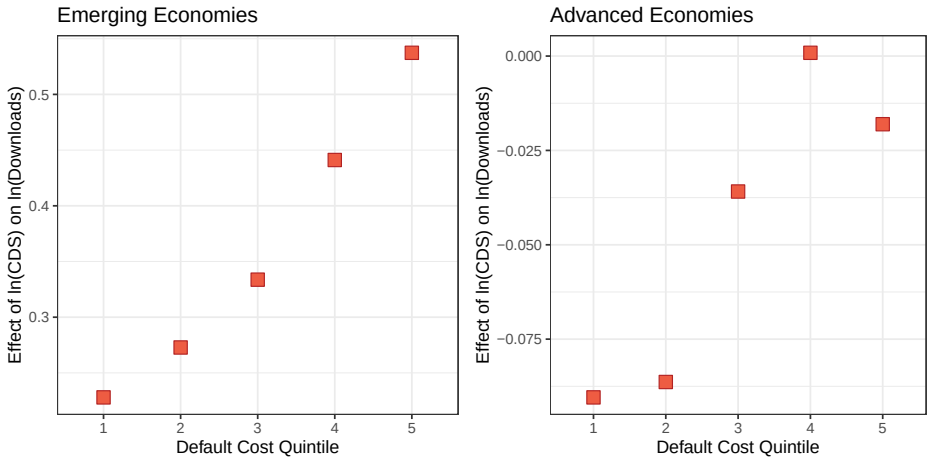
Each point corresponds to the binned mean. Fixed effects are removed from the CDS spreads, crypto app downloads and crypto app usage variables by estimating regressions of ln(CDS), ln(Downloads), ln(MAU) on country and time fixed effects, respectively. The residuals from these regressions are plotted against the local bitcoin price premium for the subset of countries with available data [von Luckner et al., 2024]. The premium measures the log difference between the bitcoin-implied dollar exchange rate and the official exchange rate. The sample is limited to beginning in January 2019 and the following subset of countries: Australia, Brazil, Canada, India, Indonesia, Japan, Mexico, South Africa, UK, US.

Figure 6: Within R-Squared Statistics from Univariate Regressions



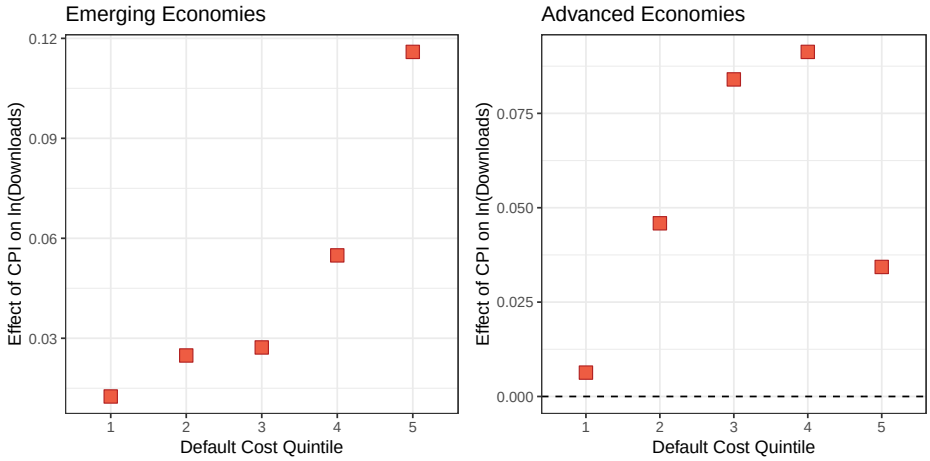
The left panel reports within R-squared from univariate fixed effect panel regressions with ln(Downloads) as the dependent variable, while right panel refers to regressions with ln(MAU) as the dependent variable. Regression specifications correspond to Equation 1. Two covariates are excluded from the tables: lagged cumulative downloads, and credit ratings FEs. These two covariates exhibit the highest within R-Squared statistics (reported in Tables 4 through 7). To keep the comparisons consistent, we exclude them from these figures, because (i) lagged downloads captures the high serial correlation in the crypto adoption data, rendering a high R-Squared value, and (ii) credit rating FEs involve several categories.

Figure 7: Crypto Downloads Sensitivity to CDS Spreads and the Social Cost of Default



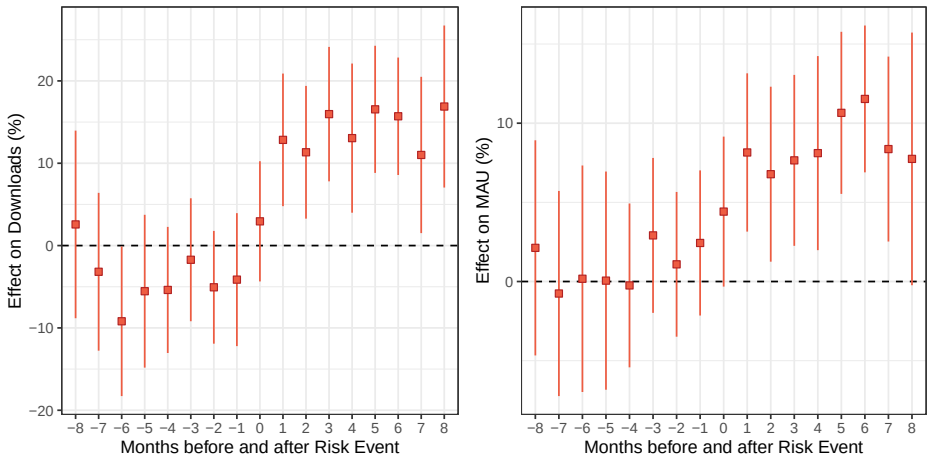
Points correspond to estimates of the coefficients β_k from the heterogeneous treatment regressions specified in Equation 3. Social cost of default is defined as the sum of public debt and bank credit to the non-financial sector, divided by GDP. Emerging market economies are: Argentina, Brazil, China, India, Indonesia, Mexico, Russia, Saudi Arabia, South Africa, Turkey. Advanced economies are: Australia, Canada, France, Germany, Italy, Japan, South Korea, United Kingdom, United States.

Figure 8: Crypto Downloads Sensitivity to CPI Inflation and the Social Cost of Default



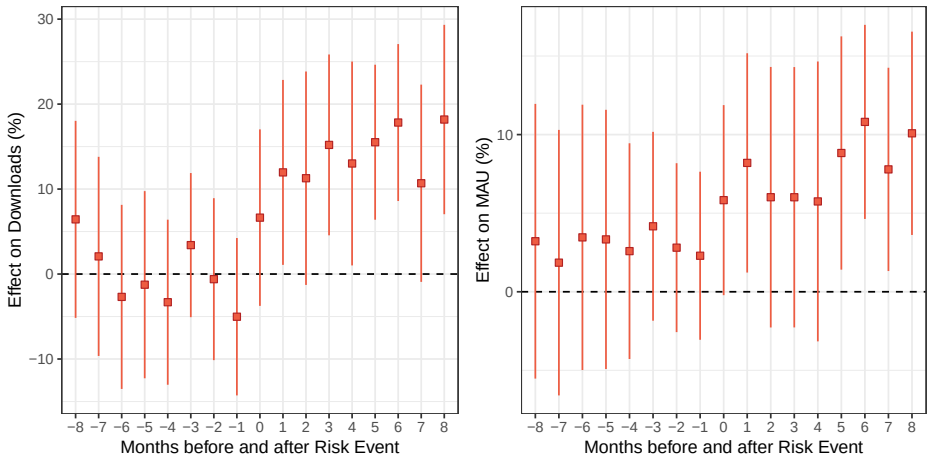
Points correspond to estimates of the coefficients β_k from the heterogeneous treatment regressions specified in Equation 3 but with ln(CDS) replaced with CPI inflation. Social cost of default is defined as the sum of public debt and bank credit to the non-financial sector, divided by GDP. Emerging market economies are: Argentina, Brazil, China, India, Indonesia, Mexico, Russia, Saudi Arabia, South Africa, Turkey. Advanced economies are: Australia, Canada, France, Germany, Italy, Japan, South Korea, United Kingdom, United States.

Figure 9: Crypto Adoption around Credit Risk Events (70th Conditional Percentile)



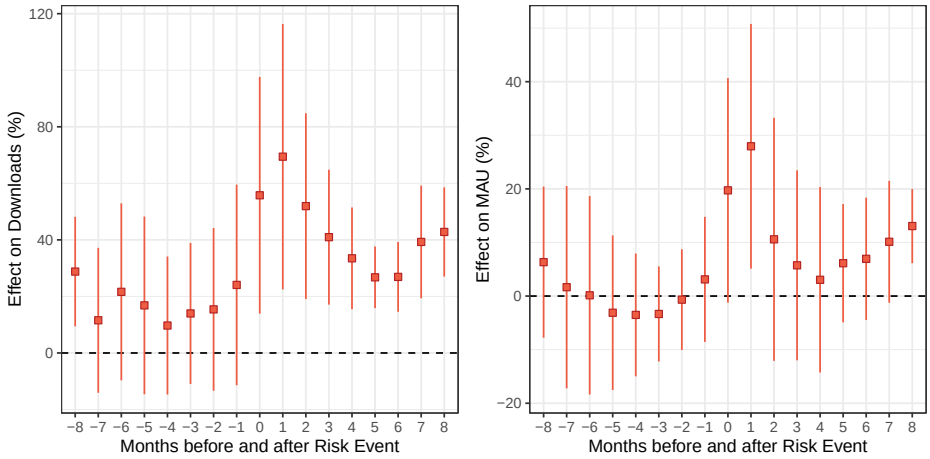
Points correspond to estimates of the coefficients ϕ_h from the event study regressions specified in Equation 4. Vertical bars correspond to 90% Driscoll-Kraay confidence bands. Credit risk events are defined as monthly CDS changes exceeding the 70th percentile of positive CDS changes.

Figure 10: Crypto Adoption around Credit Risk Events (90th Unconditional Percentile)



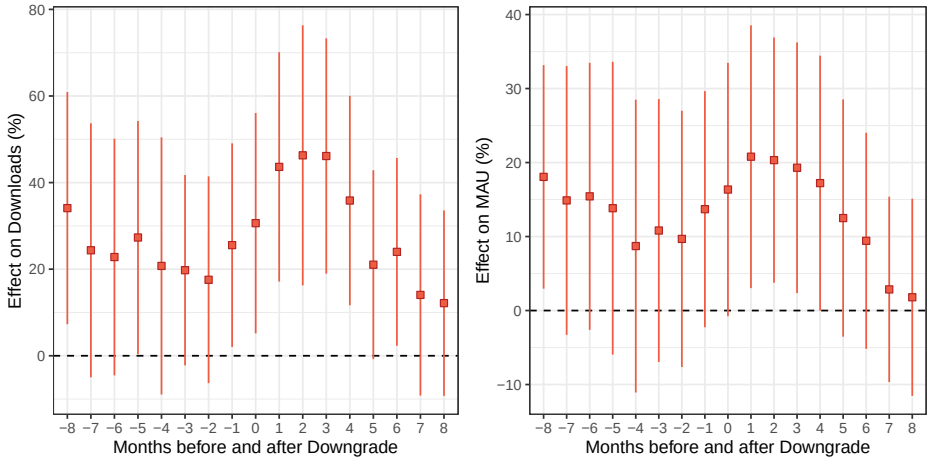
Points correspond to estimates of the coefficients ϕ_h from the event study regressions specified in Equation 4. Vertical bars correspond to 90% Driscoll-Kraay confidence bands. Credit risk events are defined as monthly CDS changes exceeding the 90th unconditional percentile.

Figure 11: Crypto Adoption around CDS Jumps (Manually Identified Credit Risk Events)



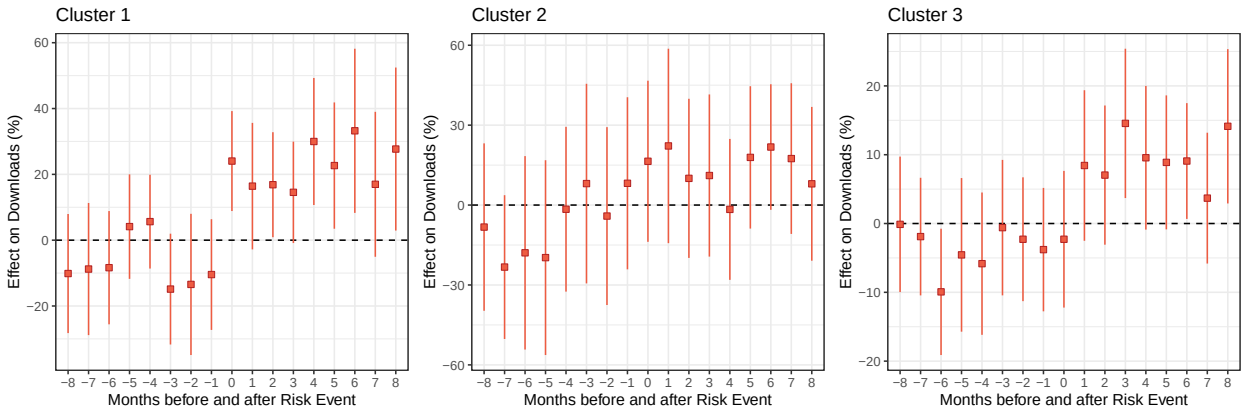
Points correspond to estimates of the coefficients ϕ_h from the event study regressions specified in Equation 4. Vertical bars correspond to 90% Driscoll-Kraay confidence bands. Credit risk events are manually identified, with list is reported in Table 10.

Figure 12: Crypto Adoption around Credit Ratings Downgrades



Points correspond to estimates of the coefficients ϕ_h from the event study regressions specified in Equation 4, but replacing risk events based on CDS jumps with Moody's credit ratings downgrades. Vertical bars correspond to 90% Driscoll-Kraay confidence bands. Credit ratings downgrades in the sample are reported in Table 11.

Figure 13: Crypto Adoption around Credit Risk Events by Cluster Subset



Points correspond to estimates of the coefficients ϕ_h from the event study regressions specified in Equation 4. Vertical bars correspond to 90% Driscoll-Kraay confidence bands. Credit risk events are defined as monthly CDS changes exceeding the 70th percentile of positive CDS changes. Clusters are identified using a k-means algorithm described in Section 4.

Table 1: Data Summary Statistics

	N	Mean	St. Dev.	Min	Max
Downloads	1,577	213.965	474.138	0.045	7,723.294
MAU	1,577	248.251	505.913	0.006	5,053.288
CDS	1,577	308.072	1,787.808	5.136	29,919.030
Central Bank Policy Rate	1,577	5.374	9.756	−0.100	83.264
CPI	1,577	5.418	9.827	−3.236	78.618
Exchange Rate	1,577	103.733	10.895	70.870	164.780
Exchange Rate Volatility	1,577	7.044	4.474	1.657	28.228
Stock Market Volatility	1,577	19.721	37.422	6.294	741.477
Public Debt/GDP	1,577	66.977	48.911	5.670	220.360
Bank Credit/GDP	1,577	77.365	40.301	9.600	184.000
Bank Sector Concentration	1,577	70.925	15.808	36.898	99.959
Stock Market Cap/GDP	1,577	92.697	73.932	8.400	345.350
Political Instability	1,577	52.291	20.841	18.669	82.219
Corruption	1,577	−0.434	0.951	−1.944	1.021
Capital Mobility	1,577	0.662	0.360	0.000	1.000
Population	1,577	241,557,006.000	401,585,896.000	23,815,995	1,417,173,173
Cellular Subscriptions	1,577	120.209	23.254	75.670	168.980
Informal Economy Size	1,577	18.973	8.404	7.950	39.750
Remittances/GDP	1,577	0.601	0.914	0.026	4.200
CDS $(-i)$	1,577	236.836	386.010	53.988	5,428.171
Central Bank Policy Rate $(-i)$	1,577	4.376	1.912	1.878	18.102
CPI $(-i)$	1,577	4.640	2.641	1.815	20.935
Capital Mobility $(-i)$	1,577	0.704	0.069	0.575	0.840
Stock Market Volatility $(-i)$	1,577	19.144	10.035	12.912	99.957
Public Debt/GDP $(-i)$	1,577	70.392	12.253	41.520	106.555
Cumulative Downloads	1,577	4,021.380	6,978.135	0.305	52,198.780

Summary statistics of (non-transformed) data. Variables indexed by $(-i)$ are constructed as the distance-weighted average of the corresponding variable from the sample of countries excluding country i as discussed in Section 2.

Table 2: Data Details

Variable	Frequency	Source	Details
Monthly average of daily active crypto app users per 100,000	Monthly	BIS and Sensor Tower	Sensor Tower is a proprietary app intelligence data provider. The data used in this paper was made publicly available by the BIS and Sensor Tower.
Crypto app downloads per 100,000	Monthly	BIS and Sensor Tower	Sensor Tower is a proprietary app intelligence data provider. The data used in this paper was made publicly available by the BIS and Sensor Tower.
5-year sovereign CDS spread	Daily	IHS Markit	USD-denominated spread. Monthly values are the average of daily observations within the month. Months with missing or zero values are observed for Argentina (default related), India, and Russia (default related). Missing or zero values are forward-filled using the most recent previous non-zero observation. Specifically, Argentina values were zero from June 1, 2020 to September 17, 2020 due to sovereign default. Argentina CDS values are missing from 2015 to March 2016 due to a 2014 sovereign default and subsequent restructuring. Argentina CDS values are missing from July 18, 2020 to September 16, 2020 due to a May 2020 default and failure to pay creditors. India is missing values in August and September 2015. Russia values were zero from June 1, 2022 to June 30, 2022 due to the Russia-Ukraine war and related financial sanctions.
Equity market risk	Monthly	Bloomberg	Computed as the standard deviation of daily MSCI local currency index returns within each month.
Central bank policy interest rate	Monthly	BIS	Nominal central bank policy rate used to construct real interest rate variable.
Year-over-year CPI inflation	Monthly	BIS	Consumer price index inflation. Also used to construct real interest rate variable.
Real effective exchange rate	Monthly	BIS	Geometric trade-weighted averages of bilateral exchange rates.
Exchange rate volatility	Monthly	BIS	36-month rolling standard deviation of monthly REER log-changes.
Population	Annual	World Bank	Annual values are used for each month within a year.
Capital mobility	Annual	Chinn and Ito (2006)	Annual values are used for each month within a year. Values range from 0 (least mobile) to 1 (most mobile) in their degree of capital mobility. Data available through 2021, so 2022 values are forward-filled using 2021 values for each country.
Political Instability	Annual	The Fund for Peace	Annual values are used for each month within a year. The Fragile States Index from the Fund for Peace. Higher values denote greater state fragility, i.e., greater political instability.
Corruption	Annual	World Bank	Annual values are used for each month within a year. The inverse of the Control of Corruption index from the World Bank's Worldwide Governance Indicators. Higher values denote greater levels of corruption.
Moody's sovereign credit ratings	Monthly	Moody's	Categorical variable combining country rating and outlook.
Bank credit to non-financial private sector as a % of GDP	Quarterly	BIS	Quarterly values are used for each month within a quarter.
Bank concentration	Annual	World Bank	Annual values are used for each month within a year. Values refer to top 5 bank assets as a percent of system-wide bank assets. Data available through 2021, so 2022 values are forward-filled using 2021 values for each country.
Cellular subscriptions	Annual	World Bank	Measures the number of mobile device subscriptions per 100 people. Values can exceed 100 when the majority of citizens have subscriptions on multiple devices. Russia data was missing for 2022, so 2021 value was forward-filled.
Informal economy size	Annual	Elgin et al. (2021)	Dynamic general equilibrium (DGE)-based estimate of informal economy sector as a % of GDP. Data is through 2020, so 2021 and 2022 values are forward-filled using observations from 2020.
Public debt to GDP	Quarterly	IMF and World Bank	World Bank QPSD database for all countries except Saudi Arabia, India, Argentina, South Korea, for which we use annual public debt to GDP data from the IMF.
Stock market capitalization as a % of GDP	Annual	World Bank	Equity market capitalization of publicly listed stocks as a percent of GDP.
Remittances as a % of GDP	Annual	World Bank	Annual values are used within each month of the year. Personal remittances received by a country as a percent of GDP.

Table 3: Contributions of Country and Time Fixed Effects to the Variation of Key Variables

	ln(CDS)	ln(Downloads)	ln(MAU)
Country FEs	0.860	0.403	0.421
Time FEs	0.032	0.503	0.504
Country+Time FEs	0.893	0.906	0.924
Panel Unit Root Test	-6.06***	-10.13***	-7.63***

Values report the R^2 statistic from regressions of the dependent variable stated in the column header on country fixed effects, time fixed effects, and both, respectively. R^2 ranges from 0 to 1. Levin et al. [2002] panel unit root tests are conducted on residuals from the regressions of key variables on country and time fixed effects, with z-statistics reported under the alternative hypothesis that the regression residuals are stationary. '*', '**', '***' correspond to the null hypothesis being rejected at the 10%, 5%, 1% significance, respectively.

Table 4: Univariate Regressions of ln(Downloads), Part 1 of 2

	Dependent variable: ln(Downloads)												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
ln(CDS)	0.367***												
	(0.070)												
CPI		0.036***											
		(0.007)											
ln(Exchange Rate)			−2.579***										
			(0.329)										
ln(Exchange Rate Volatility)				0.512***									
				(0.111)									
Real Interest Rate					−0.023***								
					(0.006)								
ln(Stock Market Volatility)						0.229***							
						(0.088)							
Public Debt/GDP							0.015**						
							(0.007)						
Bank Credit/GDP								−0.035***					
								(0.008)					
Bank Sector Concentration									−0.009**				
									(0.004)				
Stock Market Cap/GDP										−0.001			
										(0.001)			
Political Instability											0.060***		
											(0.006)		
Corruption												0.775*	
												(0.435)	
Capital Mobility													−0.444
													(0.639)
Time+Country FEs?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Credit Rating FEs?	N	N	N	N	N	N	N	N	N	N	N	N	N
Observations	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577
Within R^2	0.063	0.060	0.090	0.022	0.020	0.006	0.012	0.069	0.007	0.002	0.042	0.014	0.003

Estimates correspond to Equation 1. '*', '**', '***' correspond to 10%, 5%, 1% significance, respectively using Driscoll-Kraay standard errors.

Table 5: Univariate Regressions of ln(Downloads), Part 2 of 2

	Dependent variable: ln(Downloads)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ln(Population)	6.383***											
	(2.444)											
Cellular Subscriptions		−0.014***										
		(0.005)										
Informal Economy Size			−0.594***									
			(0.113)									
Remittances/GDP				0.276*								
				(0.147)								
ln(CDS, $-i$)					−0.069							
					(0.110)							
CPI ($-i$)						0.024						
						(0.047)						
Real Interest Rate ($-i$)							−0.010					
							(0.028)					
Capital Mobility ($-i$)								1.592				
								(2.548)				
ln(Stock Market Volatility, $-i$)									−0.850***			
									(0.148)			
Public Debt/GDP ($-i$)										0.045*		
										(0.026)		
ln(Cum. Downloads, $t-1$)											0.929***	
											(0.073)	
Credit Rating FEs												*
Time+Country FEs?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Credit Rating FEs?	N	N	N	N	N	N	N	N	N	N	N	Y
Observations	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,558	1,577	1,577
Within R^2	0.013	0.025	0.033	0.005	0.001	0.001	0.0001	0.001	0.010	0.001	0.346	0.305

Estimates correspond to Equation 1. '*', '**', '***' correspond to 10%, 5%, 1% significance, respectively using Driscoll-Kraay standard errors. Variables indexed by ($-i$) are constructed as the distance-weighted average of the corresponding variable from the sample of countries excluding country i as discussed in Section 2.

Table 6: Univariate Regressions of ln(MAU), Part 1 of 2

	Dependent variable: ln(MAU)												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
ln(CDS)	0.290***												
	(0.063)												
CPI		0.045***											
		(0.007)											
ln(Exchange Rate)			−2.981***										
			(0.409)										
ln(Exchange Rate Volatility)				0.220									
				(0.142)									
Real Interest Rate					−0.038***								
					(0.006)								
ln(Stock Market Volatility)						0.273***							
						(0.080)							
Public Debt/GDP							−0.011						
							(0.007)						
Bank Credit/GDP								−0.004					
								(0.011)					
Bank Sector Concentration									−0.009***				
									(0.003)				
Stock Market Cap/GDP										−0.004***			
										(0.001)			
Political Instability											0.024***		
											(0.008)		
Corruption												0.161	
												(0.437)	
Capital Mobility													−1.080
													(0.672)
Time+Country FEs?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Credit Rating FEs?	N	N	N	N	N	N	N	N	N	N	N	N	N
Observations	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577
Within R^2	0.036	0.087	0.111	0.004	0.051	0.008	0.006	0.001	0.007	0.030	0.006	0.001	0.016

Estimates correspond to Equation 1. '*', '**', '***' correspond to 10%, 5%, 1% significance, respectively using Driscoll-Kraay standard errors.

Table 7: Univariate Regressions of ln(MAU), Part 2 of 2

	Dependent variable: ln(MAU)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ln(Population)	−3.376											
	(3.914)											
Cellular Subscriptions		0.007										
		(0.006)										
Informal Economy Size			−1.190***									
			(0.152)									
Remittances/GDP				0.209								
				(0.136)								
ln(CDS, $-i$)					−0.156							
					(0.106)							
CPI ($-i$)						−0.124**						
						(0.062)						
Real Interest Rate ($-i$)							0.019					
							(0.049)					
Capital Mobility ($-i$)								4.902**				
								(2.460)				
ln(Stock Market Volatility, $-i$)									−0.803***			
									(0.174)			
Public Debt/GDP ($-i$)										0.015		
										(0.029)		
ln(Cum. Downloads, $t-1$)											1.371***	
											(0.049)	
Credit Rating FEs												*
Time+Country FEs?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Credit Rating FEs?	N	N	N	N	N	N	N	N	N	N	N	Y
Observations	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,558	1,577	1,577
Within R^2	0.003	0.007	0.124	0.003	0.003	0.018	0.0004	0.008	0.008	0.009	0.699	0.343

Estimates correspond to Equation 1. '*', '**', '***' correspond to 10%, 5%, 1% significance, respectively using Driscoll-Kraay standard errors. Variables indexed by ($-i$) are constructed as the distance-weighted average of the corresponding variable from the sample of countries excluding country i as discussed in Section 2.

Table 8: Multivariate Regressions of ln(Downloads) and ln(MAU)

	Dependent variable:			
	ln(Downloads)		ln(MAU)	
	Full Set	LASSO-Selected	Full Set	LASSO-Selected
ln(CDS)	0.350*** (0.097)	0.358*** (0.098)	0.282*** (0.076)	0.280*** (0.075)
CPI	0.013 (0.009)	0.011 (0.008)	−0.006 (0.007)	−0.006 (0.007)
ln(Exchange Rate)	−0.896** (0.380)	−0.829** (0.373)	0.019 (0.266)	0.023 (0.246)
ln(Exchange Rate Volatility)	−0.243 (0.150)		−0.120 (0.087)	
Real Interest Rate	0.026*** (0.008)	0.024*** (0.008)	0.003 (0.006)	0.003 (0.006)
ln(Stock Market Volatility)	0.003 (0.134)	−0.053 (0.120)	−0.181* (0.110)	−0.244** (0.101)
Public Debt/GDP	0.015*** (0.005)	0.015*** (0.005)	−0.001 (0.003)	
Bank Credit/GDP	−0.023*** (0.007)	−0.021*** (0.007)	0.007 (0.005)	0.009** (0.004)
Bank Sector Concentration	−0.016*** (0.004)	−0.016*** (0.004)	−0.018*** (0.003)	−0.019*** (0.003)
Stock Market Cap/GDP	0.001 (0.001)	0.001 (0.001)	0.0004 (0.0003)	
Political Instability	0.001 (0.009)	−0.002 (0.008)	−0.009 (0.007)	−0.009 (0.007)
Corruption	0.789** (0.307)	0.820*** (0.305)	0.131 (0.221)	0.155 (0.204)
Capital Mobility	0.525** (0.258)	0.513** (0.253)	−0.634** (0.251)	−0.614** (0.254)
ln(Population)	−1.095 (1.990)	−2.311 (1.993)	−4.456** (1.961)	−4.608** (2.032)
Cellular Subscriptions	−0.008** (0.004)	−0.009** (0.004)	−0.005 (0.003)	−0.005 (0.003)
Informal Economy Size	−0.346*** (0.126)	−0.359*** (0.127)	−0.033 (0.110)	−0.021 (0.114)
Remittances/GDP	0.675*** (0.152)	0.618*** (0.133)	0.355*** (0.120)	
ln(CDS, $-i$)	0.163 (0.104)	0.170 (0.105)	0.175 (0.112)	0.167 (0.102)
CPI ($-i$)	0.254*** (0.030)	0.247*** (0.031)	0.051* (0.029)	0.056*** (0.019)
Real Interest Rate ($-i$)	0.157*** (0.028)	0.156*** (0.027)	0.002 (0.021)	
Capital Mobility ($-i$)	−1.890* (1.036)	−2.094** (1.054)	−1.598 (2.212)	−1.700 (2.087)
ln(Stock Market Volatility, $-i$)	0.030 (0.316)		0.681*** (0.230)	0.682*** (0.214)
Public Debt/GDP ($-i$)	−0.003 (0.026)		−0.018 (0.019)	
ln(Cum. Downloads, $t-1$)	0.979*** (0.085)	0.986*** (0.087)	1.427*** (0.063)	1.437*** (0.060)
Time+Country FEs?	Y	Y	Y	Y
Credit Rating FEs?	Y	Y	Y	Y
Observations	1,558	1,558	1,558	1,558
Within R^2	0.608	0.606	0.812	0.810

Estimates correspond to Equation 2. '*', '**', '***' correspond to 10%, 5%, 1% significance, respectively using Driscoll-Kraay standard errors. Variables indexed by ($-i$) are constructed as the distance-weighted average of the corresponding variable from the sample of countries excluding country i as discussed in Section 2. LASSO-selected columns refer to OLS estimates on the set of variables identified from post-double LASSO selection.

Table 9: Multivariate Regressions of ln(Downloads) for Advanced and Emerging Market Economies

	Dependent variable: ln(Downloads)			
	Emerging Economies		Advanced Economies	
	Full Set	LASSO-Selected	Full Set	LASSO-Selected
ln(CDS)	0.594*** (0.124)	0.600*** (0.130)	0.156 (0.097)	0.195* (0.099)
CPI	0.007 (0.009)	0.007 (0.008)	−0.072 (0.070)	
ln(Exchange Rate)	−1.152* (0.614)	−1.125* (0.586)	−0.327 (0.607)	
ln(Exchange Rate Volatility)	0.106 (0.286)		−0.596** (0.232)	−0.427** (0.168)
Real Interest Rate	0.021*** (0.008)	0.021*** (0.007)	0.015 (0.064)	0.063* (0.033)
ln(Stock Market Volatility)	−0.413* (0.245)	−0.495** (0.222)	0.435*** (0.158)	0.520** (0.205)
Public Debt/GDP	0.034*** (0.008)	0.035*** (0.008)	−0.013 (0.008)	−0.015** (0.007)
Bank Credit/GDP	−0.033** (0.014)	−0.022* (0.011)	−0.020*** (0.007)	
Bank Concentration	−0.020*** (0.005)	−0.020*** (0.005)	−0.0002 (0.007)	−0.004 (0.005)
Stock Market Cap/GDP	0.001 (0.001)		−0.004* (0.002)	−0.002 (0.002)
Political Instability	0.018 (0.018)	0.004 (0.016)	0.002 (0.017)	
Corruption	0.978* (0.561)	1.195** (0.552)	1.124*** (0.320)	0.650* (0.340)
Capital Mobility	0.758** (0.343)	0.600** (0.297)	−2.547** (1.075)	
ln(Population)	−7.087 (5.613)		−8.197** (3.251)	−4.471** (2.276)
Cellular Subscriptions	0.001 (0.004)		−0.032*** (0.006)	−0.039*** (0.007)
Informal Economy Size	−0.271 (0.335)	−0.214 (0.236)	−0.921** (0.436)	
Remittances/GDP	0.531*** (0.196)	0.575*** (0.188)	1.246* (0.649)	0.895* (0.524)
ln(CDS, $-i$)	0.109 (0.172)	0.138 (0.139)	0.580*** (0.157)	0.605*** (0.124)
CPI ($-i$)	0.339*** (0.039)	0.319*** (0.037)	0.096 (0.126)	
Real Interest Rate ($-i$)	0.187*** (0.039)	0.171*** (0.030)	0.126 (0.095)	
Capital Mobility ($-i$)	−2.953** (1.435)	−3.127** (1.494)	−0.055 (2.559)	0.631 (2.672)
ln(Stock Market Volatility, $-i$)	0.517 (0.473)		−0.362 (0.357)	
Public Debt/GDP ($-i$)	−0.090** (0.038)		−0.118*** (0.036)	−0.111*** (0.032)
ln(Cum. Downloads, $t-1$)	0.954*** (0.121)	0.969*** (0.119)	0.851*** (0.104)	0.906*** (0.104)
Time+Country FEs?	Y	Y	Y	Y
Credit Rating FEs?	Y	Y	Y	Y
Observations	820	820	738	738
Within R^2	0.670	0.666	0.646	0.630

Estimates correspond to Equation 2. '*', '**', '***' correspond to 10%, 5%, 1% significance, respectively using Driscoll-Kraay standard errors. Variables indexed by ($-i$) are constructed as the distance-weighted average of the corresponding variable from the sample of countries excluding country i as discussed in Section 2. LASSO-selected columns refer to OLS estimates on the set of variables identified from post-double LASSO selection. Emerging market economies are: Argentina, Brazil, China, India, Indonesia, Mexico, Russia, Saudi Arabia, South Africa, Turkey. Advanced economies are: Australia, Canada, France, Germany, Italy, Japan, South Korea, United Kingdom, United States.

Table 10: Country-specific Credit Risk Events

Country	Date (Year-month)	CDS Spread	Note
Argentina	20-May	3062	On 22 May, Argentina failed to make a USD503-million payment of delayed interest on three bonds on the expiry of their grace periods, entering a technical default. On 26 May, both Fitch and S&P Global Ratings moved Argentina to restricted default ratings. The government is restructuring USD66 billion of its sovereign debt with private creditors.
Brazil	16-Jan	480.13	Economic and political crisis threatening to topple President Dilma Rousseff. Credit downgraded from investment grade to junk following Rousseff's move to loosen next year's budget targets, undercutting the finance minister's Joaquim Levy's austerity agenda.
Brazil	18-Sep	276.13	Sharp increase in cost to insure sovereign default in the runup to the highly anticipated and uncertain October 2018 general elections, which Bolsonaro eventually won.
Canada	16-Dec	33.27	Sharp increase in global bond yields led by the US starting in November 2016 following the US presidential election, spillover induced financial stress on Canada.
Canada	21-Oct	38.53	Canada armed forces announce COVID vaccination mandate.
China	16-Feb	136.83	Concerns over global impact of a China economic slowdown.
China	22-May	79.58	Concerns over excessive debt and China economic slowdown.
Germany	22-Jun	11.2	German inflation hit record high of 8.8% (since reunification) following 2022 Russia invasion of Ukraine and US monetary tightening (Peak Oct 2022).
France	17-Feb	49.38	French presidential elections.
United Kingdom (the)	16-Feb	34.26	Brexit referendum announcement.
United Kingdom (the)	22-Jun	10.059	UK inflation hit high of 9.6% following 2022 Russia invasion of Ukraine. Ratings agencies (S&P and Moody's) lower outlook from stable to negative, and US monetary tightening (Peak Oct 2022).
Indonesia	15-Sep	240.97	Indonesian fire crisis burned 2.6mm hectares of land between June and October (four times the size of Bali).
Italy	16-Dec	152.73	Moodys lowered outlook from stable to negative due to "slow and halting progress on economic and fiscal reform".
Italy	18-Oct	216.31	Risk of Italian debt crisis: S&P lowered outlook from stable to negative and Moodys downgraded credit from Baa2 to Baa3.
Japan	16-Feb	50.11	Risk re-pricing on worse than expected GDP numbers, and concerns over global impact of a China economic slowdown and CNY devaluation.
Japan	17-Oct	35.4	North Korean missile tests, firing missiles over Japan.
[South] Korea	16-Feb	70.437	Concerns over global impact of a China economic slowdown and CNY devaluation.
[South] Korea	17-Oct	70.99	North Korean missile tests, firing missiles over Japan.
Mexico	16-Feb	204.703	Concerns over global impact of a China economic slowdown and oil.
Mexico	18-Jun	141.64	Preceding July 1st general election.
Russia	22-Apr	12484.82	Russia invades Ukraine.
Saudi Arabia	16-Jan	185.21	Low oil prices triggering fiscal budget concerns and subsequent credit rating downgrades on outlook (S&P).
Turkey	18-Aug	455.65	Moodys and S&P downgrade Turkey's credit based on extreme Lira volatility and prolonged economic overheating and external leverage.
Turkey	22-Jun	800.6	Spiraling inflation exceeding 70% and credit downgrades from ratings agencies.
South Africa	16-Feb	353.75	Concerns over global impact of a China economic slowdown and CNY devaluation.

Table 11: Sovereign Rating Downgrades

Country	Date	Pre-downgrade Rating	Post-downgrade Rating
Argentina	Aug-19	B2 (neg)	Caa2 (stable)
Argentina	Apr-20	Caa2 (stable)	Ca (neg)
Brazil	Feb-16	Baa3 (stable)	Ba2 (neg)
China	May-17	Aa3 (neg)	A1 (stable)
France	Sep-15	Aa1 (stable)	Aa2 (stable)
India	Jun-20	Baa2 (neg)	Baa3 (neg)
Italy	Oct-18	Baa2 (neg)	Baa3 (stable)
Mexico	Apr-20	A3 (neg)	Baa1 (neg)
Russia	Mar-22	Baa3 (stable)	B3 (stable)
Saudi Arabia	May-16	Aa3 (stable)	A1 (stable)
South Africa	Jun-17	Baa2 (neg)	Baa3 (neg)
South Africa	Mar-20	Baa3 (neg)	Ba1 (neg)
South Africa	Nov-20	Ba1 (neg)	Ba2 (neg)
Turkey	Sep-16	Baa3 (neg)	Ba1 (stable)
Turkey	Mar-18	Ba1 (neg)	Ba2 (stable)
Turkey	Aug-18	Ba2 (stable)	Ba3 (neg)
Turkey	Jun-19	Ba3 (neg)	B1 (neg)
Turkey	Sep-20	B1 (neg)	B2 (neg)
United Kingdom	Sep-17	Aa1 (neg)	Aa2 (stable)
United Kingdom	Oct-20	Aa2 (stable)	Aa3 (stable)

Moody's credit ratings with outlooks in parentheses. The date column refers to month-year of the downgrade.

Table 12: K-means Clustering of Macro-financial Variables on Large CDS Jumps

Cluster	Capital Mobility	CPI	ln(Exchange Rate)	Public Debt/GDP	Bank Credit/GDP	Political Instability	ln(Stock Volatility)
1	0.393	45.492	4.649	71.791	14.531	48.948	3.877
2	0.777	1.539	4.610	89.986	112.423	47.717	2.834
3	0.336	7.225	4.652	41.980	51.508	73.092	2.986

Table reports mean values within each cluster. The k-means algorithm is stabilized by allowing for 25 random initial centroids, and then selecting the one with the lowest total within-cluster sum of squares. There are a total of 205 large CDS jumps which correspond to observations of monthly CDS changes exceeding the 70th percentile of positive CDS changes. The number of observations within clusters 1, 2 and 3 is 39, 30, 136, respectively.