Shadow Banking via Stablecoins: Evidence from the GENIUS Act

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Abstract

As of October 2025, about 98% of stablecoins by value are pegged to the U.S. dollar, yet more than 80% of stablecoin transactions occur outside the United States. As off-bank dollar liabilities, stablecoins may intensify digital dollarisation and deposit substitution, with implications for bank funding and financial stability. I study the GENIUS Act using a short-horizon event study of listed banks, relating abnormal equity returns around enactment to cross-country measures of weak money, bank fragility, and crypto adoption. These measures proxy for cross-country conditions where incentives and frictions to substitute domestic deposits into dollar stablecoins are strongest. I document that crypto adoption is positively associated with weak monetary conditions in emerging market and developing economies (EMDEs). I find no statistically significant evidence that short-horizon abnormal bank returns are more negative around enactment in countries with higher exposure or higher crypto adoption. I provide an early benchmark of how markets priced stablecoin-related risks at the time of the GENIUS Act, and a reference point for interpreting future policy shocks.

Keywords: Stablecoins, Digital Dollarisation, Deposit Substitution, Shadow Banking, Event Study, Emerging Markets

Certificate of Original Authorship

I, Nicholas Aroney, certify that this thesis has not previously been submitted for a degree, nor has it been submitted as part of the requirements for a degree except as fully acknowledged within the text. I also certify that I have written the thesis. Any help that I have received in my research work and in the preparation of the thesis has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Signature of student: Nicholas Aroney[1]

Date: 21 November 2025

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1 Introduction

Stablecoins mark a transformative innovation in digital finance: blockchain-based tokens designed to maintain a stable value, typically pegged to fiat currency. Their primary use case is to provide a digitally native, programmable form of money that combines the stability of traditional currency with the efficiency and accessibility of blockchain infrastructure (Jhanji et al., 2025). Aggregate dollar-stablecoin capitalisation exceeds US$300 billion, about 14% higher than at the end of Q2 2025 (Mathiasen & Martinez, 2025). This underscores the rapid global rise of stablecoins.

Despite being marketed as safe digital cash and a tool for financial inclusion, most stablecoin volume remains concentrated in leveraged trading, arbitrage, and DeFi activity on crypto exchanges (Bank for International Settlements [BIS], 2023a). At the same time, a growing trend is evident in emerging market and developing economies (EMDEs), where households and firms are increasingly adopting stablecoins for payments, remittances, and as a store of value (BIS, 2023b). As stablecoins become widely used forms of money, they increasingly function as an alternative to bank deposits that sit outside the regulated banking system (BIS, 2023b). This phenomenon raises a fundamental question: does the proliferation of private digital dollars siphon funding from traditional banking systems and raise instability risks, particularly where domestic money is weak or banks are fragile?

In countries beset by high inflation, currency depreciation, or limited confidence in banks, households and firms increasingly adopt USD-backed stablecoins as a safer store of value and medium of exchange (Jhanji et al., 2025). These tokens are held in digital wallets rather than domestic bank accounts, allowing users to save and transact in a stable currency without relying on local banks. In practice, stablecoins act as a digital hedge against inflation and depreciation risk. This shift is often labelled digital dollarisation: a technology-enabled extension of the classic dollarisation phenomenon whereby people in unstable monetary environments spontaneously dollarise their savings. Stablecoins may also be attractive where banking systems are fragile and domestic deposits are perceived as less safe, accessible, or reliably convertible, making nonbank stablecoins a precautionary substitute for local bank money. In this role, stablecoins compete with bank deposits and can function as "shadow deposits," privately issued dollar liabilities used like bank money but outside insured banking institutions (Wilmarth, 2023, 2025).

Uptake is visible in countries like Türkiye, Argentina, Nigeria, and Venezuela, where confidence in local money and banks is weak. In Türkiye, stablecoin purchases from April 2023 to March 2024 were about 4.3% of GDP, the highest global share (Jhanji et al., 2025). In recent years the lira has depreciated sharply, falling by 44% in 2021, 29% in 2022, 37% in 2023 and 16% in 2024 against the US dollar (Daily Sabah, 2025). Nigeria ranks second on Chainalysis' 2024 Global Crypto Adoption Index. High crypto adoption coincides with sharp naira depreciation and elevated inflation, alongside banking stress reflected in a system-wide non-performing loan ratio of about 4.5% (Chainalysis, 2024; International Monetary Fund [IMF], 2024). Although illustrative, these examples support the view that strong crypto adoption is typically observed where domestic currencies are unstable and banking systems face structural vulnerabilities.

The innovation of stablecoins has enabled a business model that is highly lucrative. Fiat-reserve stablecoin issuers collect interest on reserves that are held largely in U.S. Treasury bills and cash. They do not pass this yield to token holders. The token circulates on public blockchains and is not a deposit and does not settle in central-bank money. Issuers retain the reserve yield, so profits scale with front-end interest rates and outstanding supply. Tether is the largest stablecoin issuer. In 2025, Tether reported $10 billion in profit for the first three quarters of 2025 (Lutz, 2025). That exceeds the profitability of Bank of America, approaching that of Goldman Sachs and Morgan Stanley, despite having fewer than 150 employees (Lutz, 2025).

Analysts estimate that up to $1 trillion in bank deposits could migrate from emerging-market banks into stablecoins over the next few years (Jones, 2025). Such outflows would raise marginal funding costs, compress net interest margins, and erode franchise values if deposit betas rise and core deposits shrink. I investigate that concern by examining how a pivotal regulatory event in the United States is capitalised into bank equity returns via the channel of deposit-substitution.

A defining moment in the formalisation of stablecoins occurred in July 2025, when the United States enacted the Guiding and Establishing National Innovation for U.S. Stablecoins Act (GENIUS Act). The Act established the first comprehensive U.S. regulatory framework for payment stablecoins (U.S. Congress, 2025). By its provisions, nonbank entities and bank subsidiaries may issue stablecoins for public use, subject to reserve, disclosure, and supervisory requirements. It requires that permitted issuers maintain 100% reserve backing for their tokens in high-quality liquid assets such as U.S. currency and Treasury bills, and submit to regulatory oversight, risk management standards, and audits (U.S. Congress, 2025). It also mandates transparency via monthly disclosures of reserve holdings and redemption policies. Notably, the Act clarifies that properly regulated stablecoins are not to be treated as securities under U.S. law, carving out a distinct legal category for these digital dollar tokens. By formally integrating stablecoins into the financial regulatory perimeter, the GENIUS Act conferred a degree of legitimacy and investor protection that the stablecoin market had previously lacked (Liang, 2025).

At the same time, international policy discussion has expressed concern that the GENIUS Act could accelerate global stablecoin adoption in ways that undermine domestic monetary sovereignty and financial stability (Liang, 2025; Mathiasen & Martinez, 2025; Wilmarth, 2025). This concern echoes earlier warnings that widespread use of dollar stablecoins can intensify digital dollarisation and deposit substitution, weaken monetary policy transmission, and create bank-disintermediation and capital-flow risks, especially in EMDEs (IMF, 2022; BIS, 2023b; Copestake et al., 2023; Le et al., 2023; Wilmarth, 2023).

The GENIUS Act constitutes a distinct regulatory event that plausibly altered both the credibility and usability of stablecoins. I treat this as a plausibly exogenous shock, generated by U.S. legislative and regulatory processes unrelated to the fundamentals of foreign banking systems. The law's passage reduced legal and operational frictions for holding and transacting U.S. dollar tokens while leaving deposit insurance and lender-of-last-resort protections unchanged. This shift provides a unique opportunity to examine, in real time, how this shock is priced into bank equity returns, especially in countries where monetary and financial systems are fragile or cryptocurrency adoption is already prominent.

Within this framework, the Act offers a quasi-natural experiment that enables identification through a difference-in-differences (DiD) event-study design (MacKinlay, 1997). I define three exposure measures ex ante to capture cross-country heterogeneity in deposit substitution risk. Store-of-value weakness reflects monetary fragility, proxied by recent inflation and foreign-exchange depreciation. Bank fragility captures funding and solvency vulnerability, proxied by common equity tier 1 (CET1) capital ratios, NPL ratios, and liquidity buffers. Adoption measures the technological and behavioural readiness for on-chain finance using the Chainalysis Global Crypto Adoption Index. In economies where domestic money is a weak store of value or where banks are fragile, the improved credibility of off-bank dollar tokens raises the perceived risk of bank disintermediation. I quantify this response through the short-term return of listed banks, measured by short-horizon cumulative abnormal returns (CAR) around the Act's enactment date. As a first step, I analyse the relationship between a country's level of crypto adoption and its exposure to monetary and banking fragility. This motivates the following research questions.

RQ1 (Adoption environment): What is the relationship between a country's crypto adoption and its store-of-value weakness and bank fragility, and does this differ between advanced economies and EMDEs?
RQ2 (Market reaction to the shock): Do bank equity abnormal returns respond to the GENIUS Act enactment, and does the magnitude of the response vary with countries' store-of-value weakness and bank fragility?
RQ3 (Adoption as an amplifier): Does a country's higher crypto adoption amplify the exposure effect of the GENIUS Act on bank equity abnormal returns in the post window?

The evidence on RQ1 show that crypto adoption is generally higher in emerging market and developing economies (EMDEs) than in advanced economies and is positively associated with weaker monetary conditions. In contrast, adoption shows no strong or robust relationship with banking-system fragility. This pattern is consistent with the view that cross-country variation in crypto use is more closely tied to monetary instability—such as inflation and currency depreciation—than to weaknesses in bank capitalisation or liquidity. It also implies that the countries most exposed to potential digital dollarisation pressures are those where weak domestic money coincides with already elevated crypto adoption. This finding aligns with the emerging empirical literature emphasising stablecoin use in vulnerable monetary environments.

For RQ2, neither the cross-sectional cumulative abnormal return results nor the dynamic panel event-study estimates reveal statistically significant exposure effects in bank equity returns around the GENIUS Act shock. A wide set of robustness checks—varying abnormal-return models, aggregation weights, event windows, and sample composition—does not materially alter this conclusion. For RQ3, triple-difference specifications likewise provide no consistent evidence that higher crypto adoption amplifies exposure effects on short-horizon bank returns following enactment.

Taken together, the results suggest that, at the time of the GENIUS Act event, there is no clear evidence of large, systematic exposure-related equity response. Within the limits of this design, equity markets did not treat final passage as an immediate threat to bank franchise values through deposit substitution, even in countries combining high adoption with weak monetary conditions. This interpretation is conditional on the identified event capturing meaningful new information. The null findings are not inconsistent with the current scale and use of stablecoins, which remain small relative to global bank balance sheets and are still concentrated in trading and decentralised-finance activity. It is also possible that market participants expected the GENIUS act to integrate stablecoins into a more regulated, complementary role, with any destabilising deposit outflows viewed as contingent on future adoption and implementation.

Within this interpretation, I make three contributions. First, I provide a baseline cross-country characterisation of how crypto adoption co-varies with monetary weakness and bank fragility, and I clarify where digital dollarisation pressures are currently strongest. Second, I introduce a novel regulatory setting that uses prediction-market data to time a global stablecoin information shock, and I apply event-study and DiD methods to bank equities in a broad international sample. Third, I offer a market-based benchmark for the current phase of the stablecoin–bank nexus. At current scale, and within the limits of this design, I find that market participants do not price stablecoin-specific regulation as an immediate, first-order source of deposit-substitution or franchise-value risk for banks.

Looking forward, I frame my message as conditional and incremental rather than definitive. In my sample period, I find that the stablecoin–bank nexus remains at an early stage in listed-bank valuations. The key policy question is not whether stablecoins could matter for banks in principle, but when and through which channels they will matter in practice. If stablecoins become embedded in everyday payments and savings, I expect the mechanisms behind classic dollarisation and shadow banking to become more prevalent. In that scenario, I anticipate that shifts from insured deposits into private digital dollars could raise bank funding costs, constrain credit supply, weaken domestic banking resilience, and affect households' access to safe money and reliable payment systems. Future work should test these channels over longer horizons and with more direct measures of stablecoin use, deposits, and bank funding responses across countries. Should adoption scale further and regulation proliferate across jurisdictions, this framework can be reapplied to identify when stablecoins begin to pose material risks to bank intermediation.

2 Literature Review

2.1 Shadow Banking and Private Money

Classic banking theory highlights that banks are inherently fragile because they fund long-term illiquid assets with short-term demand deposits. In the seminal Diamond–Dybvig model, banks' liquidity transformation creates the possibility of panic runs: if all depositors demand their money at once, even a solvent bank cannot honour all withdrawals (Diamond & Dybvig, 1983). Modern shadow banking literature generalises this insight: shadow banks conduct similar maturity and liquidity transformation without central-bank backstops or deposit insurance. Pozsar et al. (2010), for example, define shadow banks as intermediaries engaging in credit intermediation via money-like liabilities but lacking access to lender-of-last-resort facilities. By this definition, stablecoins fit squarely into the shadow banking framework.

Gorton and Zhang (2023) compare stablecoins to nineteenth-century wildcat banknotes, arguing that issuing "circulating private money" makes stablecoin issuers analogous to unregulated banks whose notes may trade below par and are vulnerable to runs. In their view, stablecoins are the digital version of these private banknotes: they promise convertibility at par into dollars but rely on private issuers' credibility and asset quality rather than on public guarantees, and thus inherit the same structural fragilities. Together, these contributions place stablecoins squarely within the broader tradition of privately issued money liabilities that compete with, and sometimes undermine, public money.

From a regulatory perspective, BIS (2025) warns that today's stablecoin designs have inherent systemic risks. The BIS stresses three tests for sound money; singleness, elasticity, and integrity. Stablecoins fail each test. That judgment is consistent with observed de-pegs, issuer heterogeneity, and compliance gaps. They fragment par acceptance because stablecoins from different issuers trade at variable spreads. They are inelastic because supply expands only against pre-funded reserves. And they often dodge Know Your Customer (KYC) and Anti-Money laundering (AML) controls, compromising integrity (BIS, 2025). Additionally, these instruments promise one-for-one redemption into U.S. dollars yet sit wholly outside the traditional two-tier monetary hierarchy of central-bank reserves (Tier 1) and commercial-bank deposits (Tier 2). Stablecoins can pull retail funds out of the regulated safety net of a two-tiered monetary system and strip those funds of safeguards that make commercial-bank money safe. Unlike insured deposits, token balances carry no deposit-insurance guarantee; if the issuer fails, holders stand in line with unsecured creditors. Given that reserves backing most coins are held in opaque trust structures, the tokens lack a lender-of-last-resort. Therefore, the central bank has no legal basis or practical incentive to inject liquidity should redemptions surge (BIS, 2025).

Olk and Miebs (2025) argue that the crypto ecosystem has evolved into a credit-based shadow banking system. They argue that stablecoins play a central role in this transformation, effectively functioning as "shadow money" that substitutes for bank money within crypto markets. A key concern is that this shadow crypto banking is prone to the same cycle of boom and bust familiar from centuries of financial history. During the 2020-2022 crypto boom, for instance, private actors introduced new forms of money and credit (stablecoins, yield-bearing crypto accounts) that thrived in a lightly regulated space. When crypto markets crashed—as with the implosion of the TerraUSD stablecoin and the failure of the FTX exchange in 2022—the lack of safeguards led to devastating runs and loss of confidence. In the words of Olk, "when the bubble eventually bursts, either the state saves these new forms of currency and regulates them. . . or they vanish into thin air". By late 2022, the crypto financial system was in crisis, wiping out hundreds of billions in asset values and prompting urgent calls for a regulatory response.

In contrast, proponents suggest that well-regulated stablecoins need not pose outsized risks and can even complement the traditional system. They argue that tokenized, blockchain-based money can increase competition and efficiency in payments (Liang, 2025). For instance, stablecoins enable 24/7 instantaneous transfers and programmable transactions, potentially reducing costs for cross border payments or enabling new financial products. In principle, these innovations can occur alongside banks rather than entirely outside them. Some banks have explored issuing their own deposit-backed stablecoins or providing reserve and settlement services for stablecoin issuers, and central banks have considered designs in which such instruments are embedded within the existing monetary architecture (BIS, 2025). In this more optimistic view, fully backed tokenised payment instruments function as narrow payment rails that sit alongside commercial banks, while banks retain their core roles in deposit-taking and credit intermediation. The extent to which stablecoins evolve into regulated payment utilities integrated with existing banking structures, rather than shadow banking rivals, is a central question in the literature. This distinction is a key backdrop for assessing their implications for bank funding and financial stability.

2.2 Digital Dollarisation and Currency Substitution

A related strand of literature concerns dollarisation and currency substitution in emerging markets. Classic studies document that in high-inflation or unstable-currency environments, economic agents shift into foreign currency assets (typically U.S. dollar cash or dollar deposits) to preserve value. This phenomenon weakens the domestic currency and can undermine monetary policy effectiveness. Recent research has begun to examine how cryptoassets and stablecoins extend these dynamics into the digital realm. BIS (2023b) coins the term "cryptoisation" to describe how crypto adoption can accompany a shift from domestic currency to privately issued dollar assets. Ante et al. (2023) note that emerging-market users in countries like Turkey and Argentina with chronic inflation are likely to convert savings into U.S. dollars via stablecoins, mirroring traditional dollarisation. By offering digital access to dollars, stablecoins effectively enable "digital dollarisation." IMF analysts similarly warn that widespread use of USD stablecoins poses a risk of de facto dollarisation: people may use private digital dollars in parallel with the local currency, eroding the latter's role (IMF, 2022; Mathiasen & Martinez, 2025).

Formal macroeconomic models confirm these intuitions. Le et al. (2023) develop a two-country New Keynesian model where households in a small economy can hold a foreign-issuer stablecoin as a hedge against inflation. They find that introducing a foreign dollar stablecoin amplifies currency substitution: domestic agents hold more foreign currency units (stablecoins), reducing domestic bank deposits and increasing capital outflows under shocks. This mechanism reduces credit intermediation by domestic banks, weakens monetary policy transmission, and intensifies recessionary downturns. Similarly, Copestake et al. (2023) use a small open-economy model to show that foreign crypto assets cause significant currency substitution and deposit flight in developing economies, pressuring banks and policy. These models suggest that if a credible foreign dollar–pegged stablecoin enters circulation, it can function much like traditional dollarisation, channelling savings away from local money into crypto.

2.3 Bank Disintermediation and Financial Stability Risks

Policymakers have become increasingly concerned that off-bank digital currencies, in particular foreign-currency stablecoins, could weaken domestic banking systems in emerging markets. The Bank for International Settlements' report on financial stability risks from cryptoassets in emerging markets highlights bank disintermediation and capital flow risks as key channels through which large-scale use of cryptoassets, including stablecoins, can erode banks' funding bases and complicate monetary policy transmission (BIS, 2023b). The IMF's analysis of stablecoins similarly identifies currency substitution and bank disintermediation as first-order financial stability risks when stablecoins are used as a store of value and as a means of payment (IMF, 2022). When households and firms shift from domestic bank deposits into USD-backed stablecoins, banks lose a core source of local funding, which can constrain credit supply to the real economy and heighten vulnerability to shocks. These concerns are especially acute in emerging markets, where domestic currencies often exhibit high inflation and exchange-rate volatility, and banking systems are smaller, more dependent on retail deposits, and less able to absorb large and sudden outflows from the regulated perimeter into offshore digital dollars (IMF, 2022; BIS, 2023b)

If a significant share of money currently held as bank deposits migrates to stablecoins, banks could face sustained funding pressures that reduce their capacity to lend to the real economy (Wilmarth, 2025). Wilmarth (2025) cautions that the GENIUS Act's allowance of nonbank stablecoin issuers might accelerate this trend by legitimising stablecoins as substitutes for bank deposits. In a scenario where tech firms or fintechs issue widely adopted stablecoins, one could see "narrow banking" at scale—large pools of funds sitting in stablecoin reserves rather than in bank deposit accounts, potentially "pulling away large amounts of bank deposits" (Wilmarth, 2025). This outcome would effectively shift credit creation from traditional banks to the issuers' investment choices (often government securities or other low-risk assets), which could impair banks' capacity to extend loans to households and businesses. Moreover, the entry of Big Tech into the monetary realm (e.g. a company like Facebook attempting a stablecoin) raises the issue of huge user networks rapidly reallocating funds away from banks, undermining the longstanding policy of separating banking and commerce (Wilmarth, 2025).

On the other hand, empirical evidence to date has not shown dramatic bank disintermediation from stablecoins, largely because the stablecoin market is still small relative to the banking sector. As of 2025, U.S. bank deposits total in the tens of trillions of dollars, dwarfing the ~$0.3 trillion market capitalisation (Huther & Wang, 2025). A recent industry study by Tsyrennikov (2025) examined the relationship between stablecoin growth and community bank deposits and found no statistically significant impact so far. Using U.S. data from 2019–2025, the study tested if increases in the circulation of USDC (a major U.S.-based stablecoin) correlated with declines in community bank deposit levels, controlling for macroeconomic factors. The results showed no material erosion of bank deposits attributable to stablecoin adoption (Tsyrennikov, 2025). These findings suggest that, up to now, stablecoins have functioned largely as adjuncts to the crypto markets in the U.S. rather than competitors to mainstream bank deposits. Yet, extending the analysis beyond the U.S. is essential to assess whether the risks outlined in Section 3.2 materialise differently under structural conditions that create distinct channels for potential deposit substitution.

Recent projections highlight what is at stake. BPI Staff (2025a) compile analyst forecasts indicating that, depending on assumptions about new use cases and adoption, the market value of dollar-denominated stablecoins could range from roughly US$500 billion to about US$2 trillion by 2028, and could reach as high as about US$2.9 trillion by 2030 (BPI Staff, 2025a). Such growth, if funded largely by outflows from bank deposits, could be consequential for banks' funding structures. Drawing on calculations by Huther and Wang (2025), BPI Staff (2025a) note that, in a worst-case scenario where all stablecoin growth comes at the expense of bank deposits, U.S. banks could experience around a 10–20% decline in deposits, with larger declines possible under more aggressive growth assumptions (BPI Staff, 2025a). Even if some of the inflows into stablecoins were to come from money market funds or other sources, BPI Staff (2025a) still judge that "a substantial decline in deposits would seem likely" at the upper end of these growth projections (BPI Staff, 2025a).

Bank policy analysts further warn that, if payment stablecoin reserves are invested predominantly in short-term U.S. government debt and similar instruments rather than in bank deposits, the funds that currently support loans to households and businesses would instead finance the expansion of U.S. government debt (BPI Staff, 2025b). In such a configuration, theoretical analysis of narrow-bank-style stablecoin arrangements suggests a reduction in traditional bank credit intermediation, because stablecoin issuers would hold safe public liabilities instead of deposits that can be recycled into private lending (Liao & Caramichael, 2022). Conversely, if issuers hold a large share of their reserves as uninsured deposits at commercial banks, BPI Staff (2025a) argue that stablecoin issuers themselves could become a new class of highly run-prone wholesale creditors, so that a run on stablecoins would trigger large, correlated withdrawals from banks and significantly amplify stress in the banking system (BPI Staff, 2025a). Detailed balance-sheet simulations for euro-area banks similarly show that large, concentrated deposits from stablecoin issuers are treated as volatile funding and tighten regulatory liquidity constraints, underscoring the systemic risks associated with such deposit structures (Coste, 2024). Taken together, these scenarios motivate regulators to design safeguards that address both the loss of deposit funding and the instability of deposits linked to large stablecoin issuers before the sector scales further.

2.4 Regulatory Developments: The GENIUS Act

Given the above risks and the rapid growth of stablecoins, regulatory responses have been gaining momentum. Early U.S. policy deliberations coalesced in the President's Working Group (PWG) Report on Stablecoins (November 2021), a landmark report that outlined the perceived risks and made preliminary recommendations. The PWG—comprising the Treasury, Federal Reserve, FDIC, and OCC—highlighted run risk, payment system risk, and concentration of economic power as key issues if stablecoins were to scale as a mainstream payment method. Notably, the PWG emphasised that stablecoins at that time were "primarily used to facilitate trading of other digital assets" rather than everyday payments, but their potential future use by households and businesses warranted a comprehensive framework (President's Working Group on Financial Markets et al., 2021).

After extensive debate, the United States enacted the GENIUS Act in 2025. This was a milestone that codified the first comprehensive federal stablecoin framework. The GENIUS Act represents a more nuanced approach than the PWG's bank-only vision, reflecting compromises to accommodate innovation while addressing risks. Under the Act, stablecoin issuers have two options. They can operate as insured depository institutions (banks), or they can be nonbank firms that obtain a special licence as "payment stablecoin issuers". In practice, this means that nonbank fintech firms may issue stablecoins, but only if they are federally or state qualified under new regulatory standards, similar to credit unions or trust companies (Liang, 2025). This creates a new class of regulated nonbank financial institution dedicated to stablecoin issuance. The Act also clarifies what stablecoins are not: they are not bank deposits (and therefore are not covered by deposit insurance), are not legal tender, and are not securities, which helps narrow questions about SEC jurisdiction. Authorised stablecoin issuers face tight activity limits. They may issue and redeem stablecoins and offer closely related payment services, but they cannot engage in the broad lending and investment activities that banks undertake. The aim is to keep payment stablecoin issuers low risk and focused on payments, rather than allowing them to become leveraged intermediaries engaged in maturity transformation (U.S. Congress, 2025).

While the GENIUS Act provides statutory clarity, it delegates significant responsibility to regulators to fill in the details. It mandates that the Federal Reserve, FDIC, and Treasury (among others) draft implementing rules within 18 months on critical prudential standards. These include capital and liquidity requirements for issuers to ensure they maintain a stable value of coins, risk management standards, and provisions to uphold the "singleness of money" —essentially, maintaining confidence that a dollar in stablecoin is as good as a dollar anywhere else. Ensuring the "singleness of money" is challenging without central bank backing, but regulators are tasked to preserve parity to the extent possible (Liang, 2025). The Act also addresses competitive and systemic concerns: it instructs regulators to set limits on non-financial companies issuing stablecoins (to prevent Big Tech from gaining excessive influence via stablecoin issuance), and requires that foreign stablecoin providers seeking U.S. customers meet "comparable regulatory" standards to domestic ones (closing the door on regulatory arbitrage via offshore issuers). Additionally, AML/CFT compliance is a focus—the Act directs the Financial Crimes Enforcement Network to ensure issuers have the technological capability to enforce anti-money-laundering rules in these digital networks (Liang, 2025).

One notable provision in the GENIUS Act is the prohibition on stablecoin issuers paying interest to coin holders (U.S. Congress, 2025). This was likely included to keep stablecoins as straightforward payment instruments, not investment products that compete with bank savings accounts or money market funds. By forbidding interest on stablecoin balances, the Act aims to prevent an incentive that could dramatically accelerate deposit outflows (BPI Staff, 2025b). However, as the Bank Policy Institute pointed out, this prohibition can be circumvented by crypto exchanges or DeFi platforms, which can separately offer yield to users for parking stablecoins on their platform (BPI Staff, 2025a, 2025b). Thus, while the issuers themselves cannot advertise a yield, the ecosystem may still develop quasi-interest through other means. This an area regulators will need to monitor.

The GENIUS Act's approach has drawn mixed reactions in the literature. Proponents argue that it will bring stablecoins into the regulatory perimeter and foster greater trust, innovation, and integration of crypto-dollar markets with the traditional financial system (Liang, 2025). By providing clear rules and legitimacy for stablecoin issuers, the law could encourage more stable, fully reserved coins that might be used in mainstream payments (e.g. remittances, merchant transactions) and not just on crypto exchanges. It also positions the U.S. to be a leader in digital asset regulation, potentially propelling the digital dollar ecosystem forward in a safer manner. The optimism is that, under the Act's oversight, stablecoins could deliver on promised benefits like lower-cost cross-border transfers, financial inclusion via dollar access in underserved regions, and 24/7 payment functionality in the economy (Mathiasen & Martinez, 2025). By restricting stablecoin issuers' activities and enforcing reserve quality, the Act seeks to capture these benefits without allowing excessive risk-taking.

Critics, however, contend that the GENIUS Act stops short of what is necessary to mitigate the threats posed by stablecoins. From a financial stability standpoint, scholars like Wilmarth (2025) argue the Act "would establish a very weak and inadequate regulatory system", leaving stablecoins as uninsured, runnable liabilities that could still require bailouts in a crisis. In his view, anything less than full bank-level regulation (i.e. treating stablecoins as deposits) is insufficient. The Act's decision to let nonbanks issue stablecoins is seen as a concession to industry that could entrench shadow banking, by creating a parallel set of institutions issuing money without the full spectrum of bank regulation and safety nets. Wilmarth (2025) strongly advocates an alternative path: reject the GENIUS Act and mandate that all stablecoin issuers be FDIC-insured banks. Only by doing so, he argues, can regulators ensure stablecoins are offered in a "safe, well-regulated manner that protects consumers and maintains financial stability".

The real-world effectiveness of the GENIUS Act will depend on how well it is implemented. The Act gives regulators considerable discretion to impose prudential standards. If these rules (capital, liquidity, disclosure, etc.) are stringent, they could address many stability concerns short of forcing bank charters. Conversely, if rules end up lenient under industry pressure, the fears of shadow banking risks could be realised (BPI Staff, 2025a, 2025b; Wilmarth, 2025). The literature identifies key open questions: Will stablecoin issuers be required to hold capital buffers or insurance for their obligations? How rigorously will reserves be regulated and audited? Can regulators truly enforce parity and redemption obligations in all conditions? Also, as stablecoins potentially shift from being used mainly in crypto trading to broader payment uses, will consumer protections and financial integrity (AML/KYC) measures keep pace? These unresolved issues form a backdrop for current research and policy analysis. While the long-term impact of the GENIUS Act will depend on how regulators implement its provisions, its passage marks a regulatory turning point that invites immediate scrutiny. I treat the passage of the GENIUS Act as a regulatory information shock to bank equity markets enabling an empirical investigation into how banks react to this new information.

2.5 Empirical Literature Gaps and Contribution

Ante et al. (2023) survey 22 empirical studies on stablecoins and find that most focus narrowly on price pegs, trading arbitrage, or network behaviour. They highlight that "many important aspects of stablecoins have not yet been researched". Notably, one of the five topics they consider most significant is the use of stablecoins in emerging markets. In reviewing the academic literature on stablecoins, it becomes apparent that this is a fast-evolving topic with interests for both finance theory and public policy.

Existing literature does not provide empirical evidence that relates stablecoin adoption to domestic banking sector outcomes or examines bank equity market reactions to the GENIUS Act. Prior work mainly maps out the conceptual risks of "shadow banking via stablecoins" and considers scenarios in which stablecoins either integrate with existing banking structures or substitute for bank deposits and intermediation (BIS, 2025). The literature consists largely of theoretical models of runs and adoption, historical analogies, and forward-looking policy analyses based on assumptions rather than data. Few studies rigorously measure the real-world impact of stablecoins on banks' funding, risk, or valuations outside the U.S.

To address that gap, I provide new empirical evidence on how stablecoin adoption and stablecoin specific regulation are reflected in bank equities. First, it documents how crypto adoption varies across countries and shows how this variation relates to store-of-value weakness and bank fragility, with particular attention to EMDEs. While the general vulnerability of certain economies to digital dollarisation is well understood, this analysis provides a more precise, data-driven identification of where deposit substitution risks are most acute. Second, it treats the GENIUS Act as a stablecoin-specific regulatory information shock and uses an international bank event-study framework to examine how bank equities respond when this law is passed. By exploiting cross-country heterogeneity in monetary conditions, bank fragility, and crypto adoption, the analysis provides early market-based evidence on whether stablecoin regulation is priced as relevant for banks through the channel of deposit substitution.

Following the event-study framework in MacKinlay (1997), I apply standard event-study and difference-in-differences econometric modelling to a novel regulatory setting. This approach is consistent with recent empirical work that studies regulatory interventions through bank equity valuations and lending outcomes, such as the analysis of the ECB dividend ban by Sanders et al. (2024). By combining short-horizon cumulative abnormal returns with cross-sectional and panel difference-in-differences specifications, I provide a transparent way to assess how regulation of private digital money feeds back into banks.

If the empirical results suggest that banks in high-adoption, weak-money, and fragile systems experience more adverse equity-market reactions, this will provide early evidence that stablecoin-specific regulation is already being priced as a material risk to traditional financial institutions. If no significant equity-market reaction is observed this would suggest that suggest that markets do not yet perceive stablecoin-specific regulation as a material threat to traditional banking models. This evidence is particularly relevant for central banks and policy makers as they design stablecoin frameworks, consider cross-border spillovers from major jurisdictions, and assess how to safeguard bank-based intermediation in an environment of expanding digital private money.

To address the research questions, I formulate the following three hypotheses.

H1: Countries with higher store-of-value stress and more fragile banking systems associate with higher crypto adoption, particularly within EMDEs.
H2: Around the GENIUS Act event, banks in countries with weaker store-of-value fundamentals and more fragile banking systems experience more negative abnormal equity returns.
H3: The sensitivity of bank abnormal returns to store-of-value weakness and bank fragility is stronger in countries with higher pre-existing crypto adoption.

These predictions follow from mechanisms emphasised in the literature. Digital dollarisation research implies that when domestic currency is a weak store of value, incentives to hold dollar-denominated instruments outside domestic banks rise. Crypto and stablecoin adoption should therefore be higher where these incentives are strongest, particularly in EMDEs (H1). Banking fragility can add to this adoption motive by weakening deposit safety and making off-bank dollar claims more attractive relative to domestic deposits (H1). The GENIUS Act is treated as a stablecoin-specific information shock because it establishes a federal framework for nonbank dollar stablecoins and lowers legal and operational barriers to their use. Policy and academic analyses commonly interpret GENIUS as a credibility and frictions shock that expands the scope for deposit substitution into nonbank dollar stablecoins. Banks in more exposed monetary or fragile banking environments should therefore experience more adverse abnormal returns (H2). Integration views and implementation uncertainty could dampen the effect, though the cross-sectional prediction remains negative (H2). Narrow-banking and reserve-structure arguments further imply state dependence. Deposit substitution is easier to scale once adoption and supporting rails are already in place. Sensitivity of bank returns to monetary stress and banking fragility should therefore be strongest in high-adoption jurisdictions (H3).

3 Data and Measures

3.1 Data Sources and Sample Construction

The bank sample is drawn from Refinitiv LSEG Workspace (Refinitiv, 2025). I start from a global equity screener of active securities that are flagged as the primary quote and classified as fully paid or ordinary shares. I restrict the sample to firms whose main listing is flagged as the primary quote and whose shares are classified as fully paid ordinary shares. From this sample, I retain only companies that Refinitiv categorises as deposit-taking banks under the Thomson Reuters Business Classification. For each security I obtain the Refinitiv identifier (RIC), the company name, the country of headquarters, the country of exchange, the exchange name, the main domestic stock index RIC and the 30-day average daily value traded in U.S. dollars. I assign the ISO3 country code to each bank based on its country of headquarters. This produces a multi-country sample of listed banks in both advanced economies and EMDEs.

I construct daily return data from Refinitiv for both banks and their domestic equity benchmarks over the period January 2024 to December 2025. For each bank, I obtain the daily closing price of its primary equity listing. I also obtain the daily closing level of its main domestic equity index reported in the Refinitiv screener. This mapping links each bank to its corresponding benchmark equity index. I sort each price series by calendar date, remove observations with non-positive prices and collapse any duplicate identifiers to a single series. I then compute daily log returns for both bank and benchmark indices and retain only dates for which both returns are available.

To mitigate the influence of illiquid equities, I apply a global liquidity filter based on the 30-day average daily value traded in U.S. dollars. I compute the cross-sectional distribution of this measure across all banks with positive values and retain only those at or above the 20th percentile. This yields a panel of reasonably liquid listed banks that trade with sufficient frequency to support daily event-study analysis.

Macroeconomic and banking system data are taken from the World Bank's World Development Indicators (WDI) for inflation and exchange rates (World Bank, 2024) and from the IMF Financial Soundness Indicators (FSI) for bank capital, asset quality, and liquidity (IMF, 2024).

Crypto adoption data are drawn from the Chainalysis 2024 Geography of Cryptocurrency report (Chainalysis, 2024). Chainalysis assigns each country a rank, where a lower rank corresponds to higher adoption. This Index include over 150 countries and is based on two components: (i) on-chain transaction volumes weighted toward retail activity and (ii) peer-to-peer exchange flows. Because these components emphasise retail participation rather than institutional trading, the index captures settings where crypto is embedded in everyday payments and savings. Although the measure is not stablecoin-specific, it provides a useful proxy for a country's broader on-chain penetration and household-level propensity to use crypto rails, which are prerequisites for stablecoin adoption.

I classify countries into "advanced economies" and "emerging market and developing economies" (EMDEs) using the International Monetary Fund World Economic Outlook (WEO) economy classification (International Monetary Fund, 2025). The WEO Statistical database divide the world into two groups, advanced economies and emerging market and developing economies, and list the members of each group. I take all economies in the WEO "advanced economies" group as advanced and classify all remaining sample countries as EMDEs. This classification is widely used in policy discussions of digital dollarisation and provides an externally defined, policy relevant way to distinguish EMDEs from advanced economies in my data. Table A1 reports the resulting country composition of the event-study samples, including each country's EMDE status, the number of liquid listed banks, the exposure index, the two-day cumulative abnormal return, and the crypto adoption percentile.

Finally, to identify the timing and magnitude of the GENIUS Act regulatory shock, I use intraday prediction market prices from the Polymarket betting market for the contract "GENIUS Act signed into law in 2025?" (Polymarket, 2025). This provides a high-frequency, forward-looking measure of market beliefs about passage of the Act, which I use to anchor event time.

3.2 Construction of Key Variables

Equity returns provide a forward-looking measure of how the GENIUS Act affects the value of banks. In standard asset pricing logic, stock prices equal the discounted value of expected future cash flows, adjusted for risk, so news about regulatory changes that alters expected profitability or required returns should be reflected in bank equity prices on or around the announcement (Campbell et al., 1997; Fama, 1998). Daily equity returns are observable at high frequency and are comparable across countries, which allows the timing of the outcome to be aligned precisely with the event window. Alternative outcomes such as lending volumes, deposit flows, or accounting ratios are typically available only at quarterly or annual frequency and with substantial reporting lags, which makes them poorly suited for narrow event windows.

For each bank i and day t, the daily log return is defined as $r_{i,t} = \ln P_{i,t} - \ln P_{i,t-1}$, where $P_{i,t}$ is the closing price. I compute analogous returns $r^m_{j,t}$ for each domestic stock index j. Using the main index RIC from Refinitiv, I map each bank to a single domestic benchmark $j(i)$. The baseline abnormal return is the simple market adjusted return $AR_{i,t} = r_{i,t} - r^m_{j(i),t}$. This specification subtracts the domestic equity index from each bank's return, so that broad market movements are removed while avoiding the sampling noise that arises when bank specific betas are estimated from a limited pre-event sample (MacKinlay, 1997). To connect bank-level abnormal returns to country-level exposures, I aggregate to the country–day level. I first map each bank to its ISO3 country of headquarters. Within each country c and calendar date t I winsorise bank-level abnormal returns at the 1% tails and then compute the equal-weighted average across all banks in that country that pass the liquidity filter. I denote this average by ARc, t. I convert this average to bps and define the country–day abnormal return as $Y_{c,t} = 10{,}000 \times ARc, t$. This variable is the dependent variable in the daily DiD specifications.

For the cross-sectional analysis of the average post-shock effect in equation (2), I construct a country-level cumulative abnormal returns over the post window from event day 0 to event day 1. For each country c, I define $CAR_c(0, 1) = Y_{c,0} + Y_{c,1}$. I include only countries with observations for both event days to ensure a consistent horizon across the cross-section. This country-level cumulative abnormal return is the dependent variable in the "post-window average effect" regressions.

I aggregate bank-level abnormal returns to the country–day level because the key explanatory variables and the regulatory shock are defined at the country level. The store-of-value index, the fragility index, and the adoption measure all vary across countries but not across banks within a country. The GENIUS Act also changes the regulatory environment at the country level, not for individual banks. In this setting, bank-level regressions would treat many observations within a country as if they carried independent information, even though they share the same exposure and policy treatment. Inference would still need to cluster at the country level, so the effective number of independent units would be the number of countries rather than the number of banks (Angrist & Pischke, 2009; Wooldridge, 2010). Aggregating abnormal returns to a country–day average makes this structure explicit. It avoids overweighting large banking systems with many listed banks relative to countries with only a few banks and reduces idiosyncratic bank-specific noise that is unrelated to country-level exposure. The equal-weighted country average is therefore a natural choice for testing hypotheses about cross-country exposure to the GENIUS Act, and it aligns the level of variation in the dependent variable with the level at which exposure and treatment are measured.

I define store-of-value weakness using two components from the World Development Indicators (World Bank, 2024): consumer price inflation and exchange rate depreciation. First, I take the 2024 annual consumer price inflation rate, reported under the series code "FP.CPI.TOTL.ZG". Higher inflation indicates weaker performance of the domestic currency as a store of value. Second, I compute the percentage depreciation of the domestic currency against the U.S. dollar between 2023 and 2024 using the official exchange rate "PA.NUS.FCRF", expressed as local currency units per U.S. dollar. The depreciation rate is the percentage increase in that exchange rate between 2023 and 2024. For each country I winsorise both components at the 1 percent tails, standardise them to have mean zero and unit variance, and then take their average. I denote this composite index by $E_{sov,z}$. Higher values of $E_{sov,z}$ correspond to weaker store-of-value performance.

I define bank fragility using three components from the IMF Financial Soundness Indicators for deposit-taking institutions for 2024 (IMF, 2024). The components are the common equity tier 1 (CET1) capital ratio "FSI15_CFSI_PT", the ratio of non-performing loans to total gross loans "AQ12_CFSI_PT", and the ratio of liquid assets to short-term liabilities "FSI765_CFSI_PT". For each country I construct transformed components so that higher values always indicate greater fragility. I take the negative of the CET1 capital ratio and the negative of the liquidity ratio and keep the non-performing loan ratio with a positive sign. Each transformed series is winsorised at the 1% tails and standardised to z-scores with mean zero and unit variance. I then average the three z-scores to obtain the composite fragility index $E_{frag,z}$. Higher values of $E_{frag,z}$ reflect lower capital buffers, higher non-performing loans, and weaker liquidity positions.

The crypto adoption environment is measured using the Chainalysis 2024 Geography of Cryptocurrency country rankings (Chainalysis, 2024). As this ranking is ordinal, I transform it into a continuous measure. I let Rank_c be the rank for country c and let R_{max} be the maximum rank in the sample. I define the inverse rank $\text{InvRank}_c = R_{max} + 1 - \text{Rank}_c$, which increases in adoption, and then compute a percentile $A_{pct,c} = \text{InvRank}_c / R_{max}$. To centre this variable, I subtract its sample median and define the final adoption measure as $A_{pc,c} = A_{pct,c} - median\ (A_{pct})$. Values of A_{pc} lie approximately between minus one half and plus one half, with positive values indicating above-median crypto adoption. I use A_{pc} as the dependent variable in the cross-sectional adoption model (1) and as an interaction term in the triple-difference event-study specification (4).

Countries listed by the IMF as advanced economies are assigned an indicator of zero, while all other countries are assigned one and treated as EMDEs. All exposure indices are time-invariant over the event window. I standardise $E_{sov,z}$ and $E_{frag,z}$ at the country level, so that coefficients in regressions can be interpreted as the effect of a one standard deviation change in exposure. Table A1 reports the resulting country composition of the event-study samples, including each country's EMDE status, the number of liquid listed banks, the exposure index, the two-day cumulative abnormal return, and the crypto adoption percentile.

3.3 Stablecoin Regulatory Shock: Identification and Visualisation

The GENIUS Act proceeds through a multi-stage legislative process and generates information at several points. Equity market participants can update their expectations before final passage when hearings, committee votes, or news leaks change the perceived likelihood that the Act will become law. If I dated the event using only the formal signing date, I would ignore this learning process and risk mistiming the main information arrival. To identify the shock that is most relevant for bank valuations, I use intraday prices from a prediction market rather than a simple calendar date.

The data is obtained from the Polymarket prediction market contract "GENIUS Act signed into law in 2025?" (Polymarket, 2025). Polymarket is a decentralised, crypto-settled exchange where traders buy and sell binary claims that pay if a specified event occurs. Contract prices, scaled between 0 and 1, can be interpreted as market-implied probabilities under standard assumptions about risk neutrality and the absence of arbitrage (Snowberg et al., 2013). In this setting, the contract price reflects the consensus probability that the GENIUS Act will become law, conditional on all public and private information known at each point in time.

I transform the time series of contract prices into log-odds in order to work with an unbounded scale. I let p_t denote the contract price at timestamp t. I define the log-odds $l_t = \log(p_t/(1 - p_t))$. A unit change in l_t corresponds to a proportional change in the odds that the Act will pass.

To isolate the main information shock, I search for the largest sustained upward revision in the log-odds series ℓ_t. For each timestamp t, I compute two local medians:

$$\widetilde{\ell}_t^{pre} = (\ell_{t-H}, \ldots, \ell_{t-1}),$$
$$\widetilde{\ell}_t^{post} = (\ell_{t+1}, \ldots, \ell_{t+H}),$$

and define the sustained shift as

$$s_t = \widetilde{\ell}_t^{post} - \widetilde{\ell}_t^{pre}.$$

Intuitively, s_t measuress whether beliefs about passage move to a new level after t, rather than jumping briefly and reverting. I standardise s_t by a robust volatility estimate σ of intraday changes in ℓ_t (based on the dispersion of $\Delta\ell_t$. A timestamp is flagged as a candidate shock when$|s_t| > K\,\sigma$, with $H = 12$ observations (several hours on each side) and $K = 4$. Finally, I enforce a minimum time separation between candidates and select the one with the largest $|s_t|$as the dominant sustained increase, which I treat as the regulatory event time.

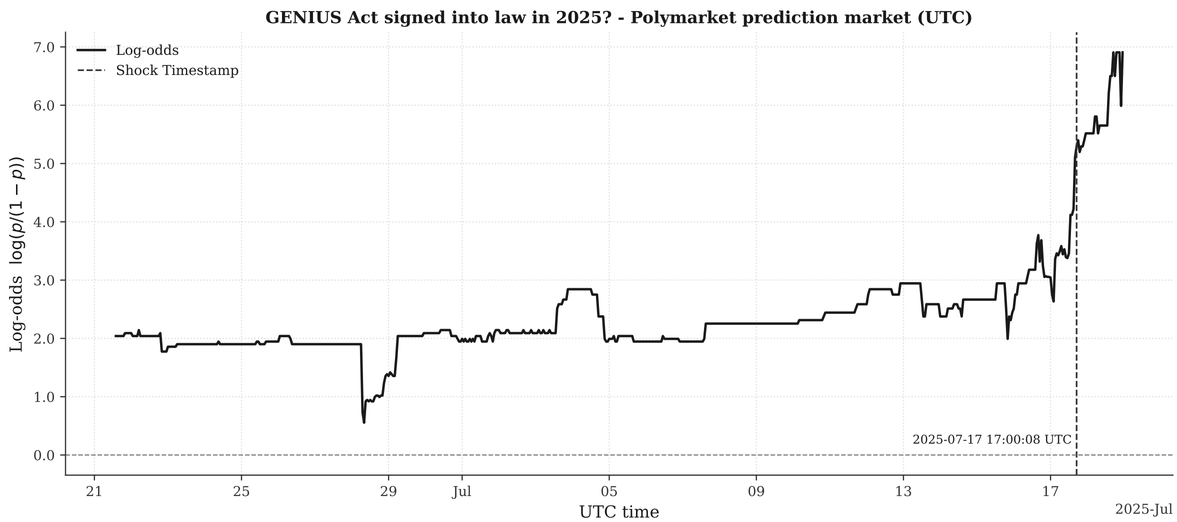

Figure 1: Prediction-market log-odds for the GENIUS Act shock.

Notes: The figure plots intraday Polymarket prices for the contract "GENIUS Act signed into law in 2025?" transformed to log-odds, $\ell_t = \log\big(p_t/(1-p_t)\big)$, where p_t is the market-implied probability of passage. The vertical dashed line marks the largest sustained upward shift in ℓ_t identified by the shock-detection algorithm and used to define the regulatory event timestamp. Event day $k = 0$ is mapped to each country's first local trading session whose market close occurs after this timestamp.

Figure 1 reports the resulting prediction-market dynamics. This plots the log-odds series for the "GENIUS Act signed into law in 2025?" contract in UTC, together with a vertical dashed line at the identified shock time. For most of the sample, the log-odds remain in a relatively narrow band between roughly 2 and 3, which corresponds to implied probabilities between about 88 and 95 per cent (Figure A1). Around mid-July 2025 there is a sharp and persistent upward movement in log-odds that the algorithm classifies as the dominant sustained increase. The identified timestamp is 17 July 2025 at approximately 17:00 UTC. At this point the log-odds increase from around 3.5 to almost 7 within a few hours, which implies a move in the passage probability from the mid-90s to effectively 100 per cent. This lines up closely with major news coverage of the bill: on 17 July 2025 Reuters published an Instant View story titled "US House sends 'Genius Act' stablecoin bill to Trump to sign", summarising market reaction to the House vote (Reuters, 2025). Instant View is Reuters' rolling format for rapid market reaction to major macro-financial news, and Reuters News is distributed globally. Therefore, it is natural to interpret the identified shock as a response to the arrival of this widely disseminated legislative news. (Refinitiv, 2025).

I interpret the dominant sustained increase in the prediction-market log-odds as the regulatory information shock that resolves remaining uncertainty about the GENIUS Act, and I treat its UTC timestamp as the event time. Because the shock is identified intraday while bank returns are measured at daily closes, I map the event moment to each bank's local trading calendar. For each bank, I set event day k=0 to the first local trading day whose market close occurs after the shock. If the shock arrives before the local close, k=0 is the same trading day because investors can react within that session. If the shock arrives after the close, or on a local weekend or holiday, k=0 is the next trading day when the market reopens. This follows standard event-study practice with daily data, where after-hours information is reflected in the next trading day's return (MacKinlay, 1997). With a shock at 17 July 2025, 17:00 UTC, U.S. and most American markets were still open, so k=0 falls on 17 July for those listings. Markets in Europe, Africa, Asia, and Oceania were already closed, so k=0 falls on their next local trading day. Any remaining asynchrony may introduce timing noise, but this mapping still yields a consistent international event window for the DiD and event-study analysis.

3.4 Sample Characteristics and Descriptive Statistics

The empirical sample is formed by intersecting four requirements: (i) listed banks whose equity meets the liquidity screen, (ii) countries with available World Development Indicators (WDI) data for constructing the store-of-value exposure, (iii) countries with available Financial Soundness Indicators (FSI) data for constructing the fragility exposure, and (iv) countries that appear in the Chainalysis crypto-adoption rankings and have sufficient equity-return coverage around the GENIUS Act shock his intersection yields 55 countries with complete information for the cumulative abnormal return and store-of-value specification, and 45 countries for the fragility specification. The resulting sample spans advanced economies and EMDEs across all major regions (Table A1).

Table 1: Descriptive statistics and correlations

Panel A: Summary statistics

Variable	N	Mean	SD	P10	P50	P90
$\mathrm{CAR}_{0,1}$	55	-1.021	97.120	-83.036	-2.636	113.636
Adoption A_{pc}	55	0.135	0.267	-0.260	0.173	0.437
E_z^{SoV}	55	0.000	1.000	-0.367	-0.270	0.130
E_z^{Frag}	45	0.000	1.000	-0.759	-0.002	0.616

Panel B: Pairwise correlations

	$\mathrm{CAR}_{0,1}$	A_{pc}	E_z^{SoV}	E_z^{Frag}
$\mathrm{CAR}_{0,1}$	1.000	-0.175	-0.124	0.242
A_{pc}	-0.175	1.000	0.226	-0.039
E_z^{SoV}	-0.124	0.226	1.000	-0.048
E_z^{Frag}	0.242	-0.039	-0.048	1.000

Notes: This table reports summary statistics (Panel A) and Pearson correlations (Panel B) for the main variables. The cumulative abnormal return $\mathrm{CAR}_{0,1}$ is measured in basis points over the $[0, 1]$ event window. Adoption A_{pc} is the median-centred within-sample adoption percentile. E_z^{SoV} and E_z^{Frag} are standardised exposure composites for the store-of-value and bank-fragility specifications, respectively. Percentiles are computed within the estimation sample. Panel B reports Pearson correlations based on all available pairs of observations (pairwise deletion).

Table 1, Panel A reports summary statistics for the country-level cumulative abnormal return, $CAR_c(0,1)$, the adoption measure A_{pc}, and the exposure indices $E_{\mathrm{sov},z}$and $E_{\mathrm{frag},z}$. The mean of $CAR_c(0,1)$ is 1 bps. Given the large dispersion, this average should not be interpreted as evidence of "no effect" by itself, but it does indicate that the typical country-level reaction is small relative to cross-country variation. The standard deviation is 97 bps, and the 10th and 90th percentiles are 83 bps and 114 bps. Some countries experience sizable negative abnormal returns while others exhibit positive reactions, pointing to economically meaningful heterogeneity in how markets price the regulatory shock.

The adoption measure A_{pc} is centred slightly above zero (mean 0.135) with a standard deviation of 0.267. High positive values correspond to countries that Chainalysis ranks near the top of its adoption index, such as Nigeria, Türkiye, and Vietnam, aligning with narratives of "cryptoisation" and "digital dollarisation" in EMDEs (BIS, 2023b; Chainalysis, 2024). Negative A_{pc}values are concentrated among high-income economies with comparatively limited use of crypto assets. Their percentile ranges show substantial cross-country variation in both store-of-value weakness and banking fragility, which is central to the exposure-based hypotheses.

Table 1, Panel B reports Pearson correlations using pairwise available observations. The correlation between $CAR_c(0,1)$ and $E_{\mathrm{sov},z}$ is 0.124, while the correlation between $CAR_c(0,1)$ and $E_{\mathrm{frag},z}$ is 0.242. These magnitudes are modest, but their signs align with the idea that countries with weaker monetary fundamentals or more fragile banking systems may be viewed as more exposed to stablecoin-related disintermediation risk. Adoption is positively correlated with store-of-value weakness (0.226), supporting the hypothesis that crypto use tends to be higher where domestic money performs poorly as a store of value. Adoption is essentially uncorrelated with fragility (0.039), suggesting that cross-country differences in crypto use are not mechanically tied to bank balance-sheet weakness.

Several limitations should be noted. The bank panel includes only listed and relatively liquid institutions, so it may under-represent vulnerabilities among small or unlisted banks. The store-of-value and fragility indices rely on annual WDI and FSI data, which may miss intra-year developments or institutional features such as deposit-insurance credibility. The Chainalysis adoption index is ordinal and based on a proprietary methodology, and my transformation from ranks to median-centred percentiles implicitly treats adjacent ranks as equally spaced. Missing WDI, FSI, or Chainalysis observations largely reflect data gaps in low-income or small economies rather than selection on equity-return outcomes. Despite these caveats, the combined dataset offers a structured setting to study heterogeneity around the GENIUS Act shock by linking bank-equity reactions to a tightly identified regulatory information event and to country-level measures of monetary weakness, banking fragility, and crypto adoption.

4 Empirical Design and Results

4.1 Adoption Environment

Before I study the market reaction to the GENIUS Act, I first characterise how crypto adoption varies across countries. This addresses RQ1 and provides the background for interpreting the return-based results. In particular, it documents how the exposure indices that later enter the event–study regressions co-move with adoption in the cross-section, and how these relationships differ between advanced economies and EMDEs.

The IMF advanced and EMDE classification is a natural way to organise the adoption results. Policy discussions of stablecoins and digital dollarisation typically emphasise their implications for EMDEs, but the underlying mechanisms, such as substitution out of local currency deposits into dollar denominated claims, are not conceptually confined to those countries. From an econometric perspective, the EMDE indicator captures broad cross-country differences in income levels and financial structures in a parsimonious way, while the continuous store of value and bank fragility indices measure variation in monetary and banking conditions both within and across these groups. The heterogeneity analysis therefore relies primarily on the exposure indices, with the advanced versus EMDE split providing a coarse but externally defined dimension along which the adoption exposure relationship may differ. (International Monetary Fund, 2025)

I use the median-centred adoption percentile $A_{pc,i}$ as the dependent variable for country i. The key explanatory variable $E_{z,i}$ denotes either the standardised store-of-value index $E_{\text{sov},z,i}$ or the standardised bank-fragility index $E_{\text{frag},z,i}$. I include an indicator EMDE_i that equals one for EMDEs and zero for advanced economies. I estimate the following pooled interaction regression:

$$A_{pc,i} = \beta_0 + \beta_1 E_{z,i} + \beta_2 \text{EMDE}_i + \beta_3 (E_{z,i} \times \text{EMDE}_i) + \varepsilon_i. \tag{1}$$

I estimate equation (1) by ordinary least squares and report heteroskedasticity-robust HC3 standard errors (MacKinnon & White, 1985). HC3 standard errors are used because cross-country data are likely to exhibit heteroskedasticity and influential observations. HC3 offers improved finite-sample properties compared to conventional Eicker–White corrections (MacKinnon & White, 1985). In this specification, β_1 is the exposure–adoption slope for advanced economies, $\beta_1 + \beta_3$ is the slope for EMDEs, and β_2 captures the EMDE–advanced difference in adoption at the mean exposure level ($E_{z,i} = 0$).

H1 predicts $\beta_1 \geq 0$ and $\beta_1 + \beta_3 > 0$, with $\beta_3 > 0$ indicating that adoption responds more strongly to exposure in EMDEs.

Table 2: Adoption and Exposure with EMDE Interaction

	Panel A: Store-of-Value $E_{\text{sov},z}$	**Panel B: Bank Fragility** $E_{\text{frag},z}$
Advanced slope ($\beta_A = \beta_1$)	0.030 (0.850)	−0.118 (0.184)
EMDE slope ($\beta_E = \beta_1 + \beta_3$)	0.051** (0.025)	−0.023 (0.070)
Slope difference ($\Delta = \beta_3$)	0.021 (0.851)	0.095 (0.197)
EMDE level (β_2)	−0.100 (0.240)	0.109 (0.082)
Observations (N)	144	68
R^2	0.045	0.030

Notes: This table reports pooled OLS regressions of adoption on the standardised exposure composite, an EMDE indicator, and their interaction. The dependent variable is A_{pc}, the median-centred adoption percentile. Each panel uses the exposure shown in the column header ($E_{\text{sov},z}$ in Panel A and $E_{\text{frag},z}$ in Panel B). Heteroskedasticity-robust (HC3) standard errors are reported in parentheses. "Advanced slope" is the marginal effect of exposure for advanced economies (β_1); "EMDE slope" is the marginal effect for EMDEs ($\beta_1+\beta_3$); "Slope difference" is the difference between EMDE and advanced slopes (β_3); "EMDE level" is the EMDE–advanced intercept difference at E=0 (β_2). *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

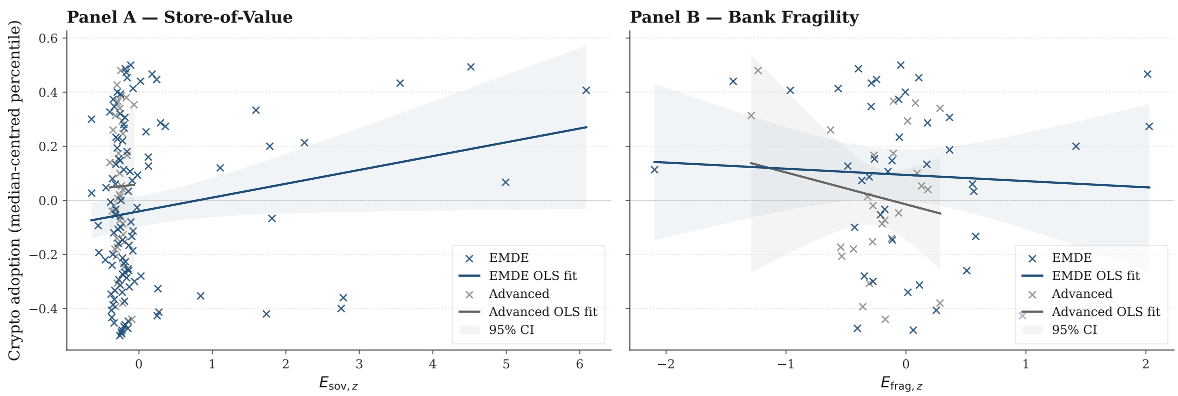

Figure 2: Crypto Adoption and Exposure with EMDE Interaction.

Notes: This figure plots the median-centred crypto adoption percentile A_{pc} against (Panel A) store-of-value weakness $E_{\mathrm{sov},z}$ and (Panel B) bank fragility $E_{\mathrm{frag},z}$. Solid lines show within-group OLS fits for advanced economies and EMDEs from equation (1); shaded bands denote 95% confidence intervals for the fitted mean using HC3 robust standard errors.

The two panels of Table 2 and Figure 2 use different country samples. Panel A includes 144 countries for which both adoption and the store-of-value composite are available. Panel B includes 68 countries because the fragility index requires IMF Financial Soundness Indicator data, which are only reported for a subset of jurisdictions. The adoption regressions in this section therefore use a broader cross-country sample than the event-study return analysis in Sections 4.2–4.5, which is restricted to countries that have exposure and adoption data and sufficiently liquid listed banks that meet the return-data requirements.

Store-of-value

Panel A of Table 2 and Figure 2 set $E_{z,i} = E_{\mathrm{sov},z,i}$. For advanced economies, the exposure–adoption slope is small and imprecise: the advanced slope is 0.030 (SE = 0.850) and is not statistically significant at the 10% level. Economically, a one-standard-deviation increase in the store-of-value index is associated with only a 3-percentile-point change in adoption among advanced economies, which is negligible relative to the cross-country dispersion in A_{pc} (Table 1).

For EMDEs, the slope is larger and precisely estimated. The EMDE slope is 0.051 (SE = 0.025), statistically significant at the 5% level. Thus, a one–standard-deviation increase in store-of-value stress is associated with an increase of around 5 percentile points in crypto adoption for EMDEs. The EMDE intercept difference at average exposure is −0.100 (SE = 0.240), which is not statistically significant at the 10% level, indicating that at average store-of-value conditions adoption levels in EMDEs and advanced economies are similar.

The formal test of a slope difference across groups is weak. The slope difference (interaction term) is 0.021 (SE = 0.851) and is not statistically significant at the 10% level. Nonetheless, the point estimates and Figure 2, Panel A, show a clear pattern: the fitted line for EMDEs slopes upward across the observed range of $E_{\mathrm{sov},z}$, while the advanced-economy line is nearly flat and lies within a wide confidence band. In practice, the positive association between store-of-value stress and adoption comes almost entirely from the EMDE subsample. The model explains only a modest share of cross-country variation in adoption ($R^2 = 0.045$), which is consistent with the parsimonious specification and the noisy nature of cross-country adoption data.

Bank fragility

Panel B of Table 2 and Figure 2 set $E_{z,i} = E_{\mathrm{frag},z,i}$. In this case, neither group exhibits a statistically meaningful exposure–adoption slope. For advanced economies, the advanced slope is −0.118 (SE = 0.184) and is not statistically significant at the 10% level. For EMDEs, the EMDE slope is −0.023 (SE = 0.070), also not statistically significant at the 10% level. The slope difference is 0.095 (SE = 0.197) and again is not statistically significant at the 10% level, so there is no evidence of a differential sensitivity of adoption to fragility across income groups.

The EMDE intercept difference at average fragility is 0.109 (SE = 0.082). This estimate implies that, at $E_{\mathrm{frag},z} = 0$, EMDEs have crypto adoption percentiles roughly 11 points higher than advanced economies, but the coefficient is not statistically significant at the 10% level. The fitted lines in Figure 2, Panel B, are almost flat and accompanied by wide confidence bands, which confirms that cross-country differences in the fragility composite are not systematically associated with adoption once EMDE status is controlled for.

Interpretation

The adoption regressions show that adoption is more strongly associated with store-of-value stress in EMDEs than in advanced economies, while the bank-fragility composite does not exhibit a strong relationship with adoption in either group. As discussed above, point estimates for the EMDE intercepts also indicate higher adoption at average exposure, although these level differences are not precisely estimated.

In relation to H1, the evidence provides partial support. Within EMDEs, adoption increases with store-of-value stress in a way that is statistically and economically significant at conventional levels. This is consistent with households and firms using crypto assets and stablecoins to hedge inflation and currency depreciation. At the same time, there is no robust association between adoption and bank fragility, and the formal tests do not indicate large differences in exposure slopes between EMDEs and advanced economies. The limited explanatory power of the regressions and the imprecision of some coefficients underline that these patterns should be viewed as descriptive rather than definitive.

From an econometric perspective, equation (1) is best interpreted as a descriptive characterisation of how adoption co-varies with monetary and banking conditions, rather than as a structural model. The results suggest that the store-of-value and fragility indices capture distinct dimensions of the macro-financial environment, with adoption primarily linked to the monetary dimension. For RQ1, the main conclusion is that, in this sample, crypto adoption tends to be higher in EMDEs and is more closely associated with weaker store-of-value conditions than with weaker banking conditions. In the subsequent event-study analysis, the store-of-value and fragility indices enter as separate exposure variables, allowing bank-equity returns around the GENIUS Act shock to be related to each underlying dimension in turn.

4.2 Average Post-Shock Effect on Bank Equity

I test RQ2 in a reduced-form event-window cross-section by relating the two-day cumulative abnormal return, $\mathrm{CAR}_i(0,1)$, to the exposure indices. I examine whether countries with weaker monetary and banking conditions experience more negative bank equity returns in the immediate short-run period following the GENIUS Act shock. This specification provides a transparent benchmark for H2 before I test the dynamic panel event-study. For each country i, I estimate the following regression separately for store-of-value weakness and bank fragility:

$$\mathrm{CAR}_i(0,1) = \alpha + \beta E_{z,i} + \varepsilon_i. \tag{2}$$

The dependent variable $\mathrm{CAR}_i(0,1)$ is the cumulative abnormal return in basis points from event day $k = 0$ to $k = 1$. I estimate equation (2) by ordinary least squares with heteroskedasticity-robust HC3 standard errors (MacKinnon & White, 1985). The regressor $E_{z,i}$ denotes either the standardised store-of-value index $E_{\mathrm{sov},z,i}$ or the standardised bank-fragility index $E_{\mathrm{frag},z,i}$. I aggregate bank-level abnormal returns to the country level before estimation, so each country contributes a single observation to the cross-section. The slope coefficient β measures the effect of a one-standard-deviation change in exposure on the two-day post-shock CAR in bps. A value of $\mathrm{CAR}_i(0,1) = -50$ therefore corresponds to a 0.5% cumulative underperformance of banks in country i relative to the domestic equity benchmark over the two trading days after event.

The event window 01 is chosen to capture the short-run return of banks after the GENIUS Act shock while accommodating the mapping from the intraday UTC timestamp to local trading days. A two-day window reduces the influence of microstructure noise relative to a single-day reaction and allows equity markets in non-US time zones to incorporate the information shock in the first full trading day after it becomes common knowledge (MacKinlay, 1997). At the same time, it remains short enough that confounding macroeconomic or policy news is less likely to dominate the return variation. The cross-section includes only countries that (i) have complete exposure data and (ii) satisfy the return-data requirements for constructing $\text{CAR}_i(0,1)$; that is, I require non-missing, liquidity-screened abnormal returns for both event days $k = 0$ and $k = 1$ in a country. The resulting country composition of the store-of-value and fragility event-study samples is summarised in Table A1, Panels A and B.

H2 predicts $\beta < 0$ for both exposures where countries with weaker money or more fragile banks should display more negative post-window cumulative abnormal returns.

Table 3: Post-Window Cross-Section: CAR(0–1) on Exposure

	Panel A: Store-of-Value (SoV)	**Panel B: Bank Fragility**
Exposure (β)	−11.3 (12.8)	45.5 (44.3)
Observations (N)	55	45
R^2	0.015	0.059
Adj. R^2	−0.003	0.037

Notes: This table reports cross-sectional OLS regressions of the post-window cumulative abnormal return, CAR(0–1), on standardised exposure composites. The dependent variable is CAR(0–1) in basis points, measured over event days $k \in [0,1]$. Panel A uses the store-of-value exposure $E_{\text{sov},z}$; Panel B uses the fragility exposure $E_{\text{frag},z}$. Heteroskedasticity-robust (HC3) standard errors are reported in parentheses. Coefficients and standard errors are expressed in basis points and rounded to one decimal place. Intercepts are estimated but not reported. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Store-of-value

Table 3, Panel A reports the results for store-of-value weakness. The sample contains 55 countries that satisfy the data requirements for both the event window and the store-of-value composite. The estimated coefficient on $E_{\text{sov},z,i}$ is -11.3 bps (SE = 12.8). This coefficient is not statistically significant at the 10 percent level. Economically, a one-standard-deviation increase in the store-of-value index is associated with an 11.3 bps decline in the two-day post-shock cumulative abnormal return. This effect is small when compared with the cross-country distribution of $\text{CAR}_i(0,1)$ in Table 1, Panel A, where the standard deviation is close to 100 bps and the 10th–90th percentile range spans roughly -80 to $+110$ bps. The R^2 of 0.015 (and slightly negative adjusted R^2) indicates that, in this simple one-regressor specification, variation in the store-of-value composite accounts for only a modest fraction of the observed cross-sectional dispersion in two-day abnormal returns, which remain largely idiosyncratic at this horizon.

Bank fragility

Panel B uses the bank-fragility index $E_{\text{frag},z,i}$ as the exposure. The sample reduces to 45 countries because the fragility composite requires IMF Financial Soundness Indicator data on capital, non-performing loans, and liquidity that are not available for all jurisdictions. The estimated coefficient is 45.5 bps (SE = 44.3). This coefficient is also not statistically significant at the 10 percent level. The positive sign runs against the directional prediction in H2, which anticipates more negative post-shock bank returns in more fragile systems. However, the estimate is imprecise. The large standard error again implies a wide confidence band that is consistent with economically small negative effects, negligible effects, or positive effects. The R^2 rises to 0.059 (adjusted R^2 = 0.037) in the smaller sample, but the overall fit remains limited: most of the cross-country variation in $\text{CAR}_i(0,1)$ is not captured by the fragility index alone.

Interpretation

Taken together, the coefficients and standard errors in Table 3 provide little evidence that the GENIUS Act generates a strong, unconditional linear relationship between short-horizon bank cumulative abnormal returns and the composite exposure measures. In this reduced-form cross-section, the data do not support H2: neither store-of-value weakness nor bank fragility is associated with statistically or economically large differences in $\text{CAR}_i(0,1)$.

At the same time, the null result should be interpreted cautiously and primarily as descriptive. The cross-section contains only 55 countries for the store-of-value regression and 45 for the fragility regression, which limits statistical power. The exposure variables are composite indices constructed from annual macroeconomic and supervisory data and are likely measured with error; under classical measurement error, noise in $E_{z,i}$ attenuates the estimated slope toward zero in equation (2) and biases against detecting significant effects (Wooldridge, 2010). The effect of the GENIUS Act may also vary over event time or depend on the crypto adoption environment, features that a static, one-factor cross-section cannot capture. Finally, a two-day event window may be too short for equity markets to fully incorporate the implications of a structural regulatory change, particularly when the main channel operates through gradual deposit substitution and business-model adaptation rather than immediate cash-flow shocks (MacKinlay, 1997).

For these reasons, I view equation (2) and Table 3 as a descriptive benchmark rather than as the definitive test of RQ2. I therefore turn to a richer DiD design that exploits the full daily panel of abnormal returns, interacts exposure with event-time indicators, and includes country and day fixed effects. This panel framework traces the dynamic response of bank equity around the prediction-market shock, to test formally for pre-event parallel trends, and to examine whether exposure loads more strongly in the post window once common shocks and time-invariant country heterogeneity are removed.

4.3 Dynamic Exposure Effect around the Shock

I revisit RQ2 with a dynamic DiD specification that relates daily abnormal bank equity returns to exposure and event time. This framework exploits the full country–day panel around the GENIUS Act shock and removes both time-invariant cross-country heterogeneity and common global shocks. It therefore aims to marginally sharpen identification relative to the cross-sectional CAR regressions in Section 5.2 (Angrist & Pischke, 2009; MacKinlay, 1997; Wooldridge, 2010).

Let $Y_{i,k}$ denote the abnormal bank equity return in bps for country i on event day k. Let $E_{z,i}$ denote either the standardised store-of-value index $E_{\text{sov},z,i}$ or the standardised bank-fragility index $E_{\text{frag},z,i}$. I estimate the following event-time regression separately for each exposure measure:

$$Y_{i,k} = \alpha_i + \delta_k + \sum_{\ell \neq k_0} \beta_\ell \left(E_{z,i} \times 1\{k = \ell\} \right) + u_{i,k}, \tag{3}$$

where α_i are country fixed effects, δ_k are event-time fixed effects, and $k_0 = -1$ is the omitted baseline day. The coefficient β_k measures the change, on event day k, in the slope of abnormal returns with respect to exposure relative to the pre-event baseline.

Country fixed effects remove time-invariant heterogeneity in bank risk, banking structure, and regulatory environment that might be correlated with exposure. Day fixed effects absorb any global news or market-wide shocks that affect all countries on a given event day, including macroeconomic announcements and general volatility around the GENIUS Act process. Identification therefore comes from within-country movements in returns around the shock that are differentially related to exposure, conditional on these fixed effects. I estimate equation (3) using a fixed effects panel estimator and cluster standard errors at the country level. With 19 event days in the store-of-value panel and 16 in the fragility panel, the number of time clusters is small, so two-way clustering by country and day would produce unstable covariance estimates. Clustering on countries is appropriate because exposure varies only across countries and because daily returns can exhibit serial correlation and heteroskedasticity within country (Angrist & Pischke, 2009; Wooldridge, 2010).

As a summary of the immediate post-event impact, I also estimate a specification that averages the exposure effect over the two-day post window:

$$Y_{i,k} = \alpha_i + \delta_k + \beta^{\text{post}} \left(E_{z,i} \times \text{Post}_k \right) + u_{i,k}, \tag{4}$$

where $\text{Post}_k = 1\{k \in [0,1]\}$. The coefficient β^{post} is the difference between the exposure slope in the two-day window $k \in [0,1]$ and the baseline day $k = -1$. H2 predicts $\beta_k < 0$ for $k \geq 0$ and $\beta^{\text{post}} < 0$ for both exposure measures: more exposed countries should experience more negative abnormal returns once the GENIUS Act information arrives.

Table 4: Dynamic DiD with Fixed Effects: Post-Window Average Exposure Slope

	Panel A: Store-of-Value	**Panel B: Bank Fragility**
$E_z \times$ Post	−3.2 (5.18)	16.0 (18.45)
Pretrend Wald p	0.080	0.880
Observations (country–day)	608	498
Entities (countries)	55	45
Time periods (dates)	19	16
Within R^2	0.0003	0.0009

Notes: This table reports post-event average exposure coefficients from a dynamic difference-in-differences event-study specification estimated by PanelOLS with country and day fixed effects. The dependent variable is the daily abnormal bank equity return, in basis points. "$E_z \times$ Post" is the average of the post-event exposure coefficients over $k \in [0,1]$, relative to the pre-event baseline period $k_0 = -1$. E_z^{SoV} (Panel A) and E_z^{Frag} (Panel B) are the standardised store-of-value and fragility exposure indices, respectively. Standard errors are clustered at the country level and reported in parentheses. "Pretrend Wald p (all $k < 0$)" reports the p-value from a joint test that all pre-event exposure coefficients are equal to zero. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The store-of-value panel contains 608 country-day observations from 55 countries. Each country is observed over an 11-day event window $k \in [-5,5]$ around the GENIUS Act shock. Because the intraday shock maps to different local sessions (same-day $k = 0$ in the Americas and next-day $k = 0$ elsewhere), this window spans 19 distinct calendar trading dates across countries. The fragility panel contains 498 observations from 45 countries over the same event window, spanning 16 calendar trading days; the smaller sample reflects more limited FSI coverage.

Average post-event exposure effect

Table 4 reports estimates of equation (4). For the store-of-value specification, the post-window coefficient on $E_z \times$ Post is −3.2 bps per one–standard-deviation increase in exposure (SE = 5.18), which is not statistically significant at the 10% level. For the bank-fragility specification, the corresponding estimate is 16.0 bps (SE = 18.45), also not statistically significant at the 10% level. In both panels, the within-R^2 is close to zero, which is expected in a high-frequency return panel with country and day fixed effects and a single time-invariant exposure interaction. Overall, the post-window estimates do not indicate a clear negative exposure gradient in two-day abnormal returns of the sign implied by H2.

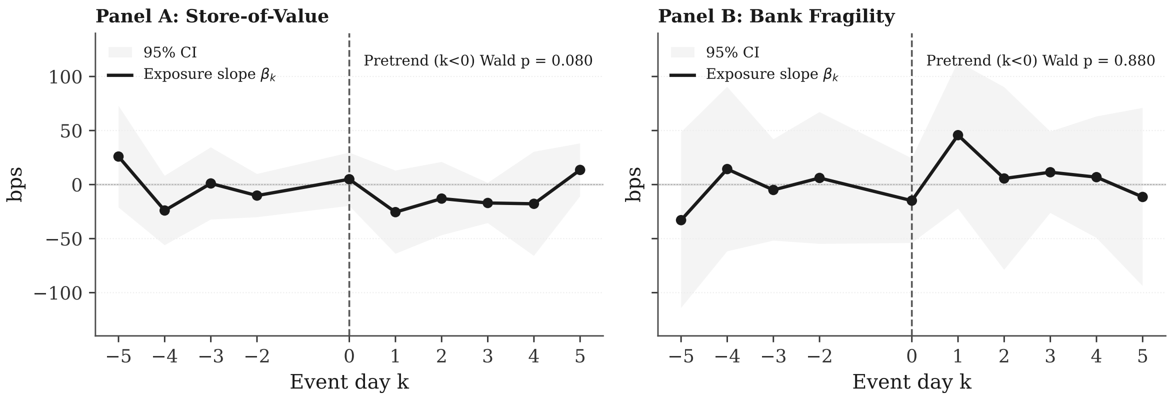

Figure 3: Event-Time Exposure Coefficients Around the GENIUS Act Shock.

Notes: Points show dynamic DiD estimates of β_k from equation (3), measuring how daily abnormal bank returns $Y_{i,k}$ load on exposure at each event day k relative to the baseline $k = -1$. Abnormal returns are country-level averages of market-adjusted bank returns, expressed in basis points. Error bars denote 95% confidence intervals based on standard errors clustered by country. Panels report results separately for store-of-value exposure $E_{\text{sov},z}$ and bank-fragility exposure $E_{\text{frag},z}$.

Figure 3 plots the full event-time profile of β_k from equation (3), and Table A2 reports the underlying coefficients. Around the event, the point estimates are small relative to their standard errors. In the store-of-value specification the coefficients at $k = 0$ and $k = 1$ are 4.9 bps (SE = 12.57) and −25.5 bps (SE = 19.63), respectively; in the fragility specification, the corresponding estimates are −14.9 bps (SE = 19.99) and 45.7 bps (SE = 34.68). None of these post-event coefficients are statistically different from zero at the 10 percent level, and the 95 percent confidence intervals around β_k for $k \geq 0$ span zero in both panels (Figure 3; Table A2).

The DiD interpretation of equation (3) requires that, absent the GENIUS Act shock, countries with higher and lower exposure would have followed parallel paths in abnormal returns, conditional on the fixed effects. I assess this assumption using joint Wald tests of the pre-event exposure coefficients. For the store-of-value specification, the hypothesis that all pre-event coefficients are zero has a p-value of 0.080. For the fragility specification, the corresponding p-value is 0.880. At the 5% level, I do not reject the null of zero pre-event slopes in either case. At the 10% level, the store-of-value test is marginal, which I interpret as weak evidence that some pre-event coefficients may deviate slightly from zero but without a clear pattern. The pre-event point estimates are individually imprecise, and their magnitudes are comparable to those in the post period, so the pre-trend diagnostics are broadly consistent with, but do not strongly reinforce, the parallel-trends assumption (Figure 3; Table A2).

Interpretation

The dynamic panel results do not support H2, and RQ2 remains unsubstantiated. Conditional on country and day fixed effects, neither store-of-value weakness nor bank fragility generates a statistically or economically large negative exposure slope in daily abnormal bank returns in the two days following the GENIUS Act shock. The estimated post-event exposure coefficients are small relative to their standard errors and, where statistically different from zero, they do not line up in a way that is consistent with a monotonic, adverse adjustment for more exposed countries. This is consistent with the literature's integration view and with uncertainty over how strictly GENIUS will be implemented. The absence of a dynamic exposure gradient implies that, at this margin, market participants do not revise bank franchise values more in weak-money or fragile-bank environments. Any disintermediation effects must either be too small to detect in short-run prices, already priced before the shock, or contingent on implementation and scale.

From an econometric perspective, the dynamic specification in equations (3) and (4) marginally strengthen identification relative to the cross-sectional regression in Section 4.2 by exploiting the full panel, absorbing time-invariant country heterogeneity and common shocks, and providing explicit pre-trend tests. The fact that the results remain null in this setting suggests that any heterogeneous effect of the GENIUS Act on bank equities that operates through the store-of-value and fragility indices is either very small in the short run or too imprecisely estimated to be distinguished from zero in this sample. This outcome is consistent with the view that very short-horizon event windows have low signal-to-noise ratios in returns and that even moderate measurement error in composite exposure indices attenuates slope coefficients toward zero (MacKinlay, 1997; Wooldridge, 2010).

At the same time, these average exposure effects do not rule out more nuanced forms of heterogeneity. Section 4.1 shows that adoption responds more strongly to store-of-value weakness in EMDEs than in advanced economies. Motivated by this pattern, Section 4.4 extends the empirical design to a triple-difference specification that interacts exposure with crypto adoption. This specification asks whether the GENIUS Act has more pronounced adverse equity effects in countries that combine weak monetary or banking conditions with high crypto adoption and shifts the focus to the amplification role of adoption.

4.4 Adoption as an Amplifier of Exposure

To address RQ3 I test whether a countries crypto adoption amplifies the effect of exposure on bank equity abnormal returns around the GENIUS Act shock. I allow the exposure slope to vary both with event time and with the adoption level. Let $Y_{i,k}$ again denote the abnormal bank equity return in basis points for country i on event day k. Let $E_{z,i}$ denote either $E_{\text{sov},z,i}$ or $E_{\text{frag},z,i}$, and let A_i denote the median-centred adoption percentile $A_{pc,i}$. For each exposure measure I estimate the dynamic triple DiD specification:

$$
\begin{aligned}
Y_{i,k} = \alpha_i + \delta_k + \sum_{\ell \neq k_0} \gamma_\ell \left(E_{z,i} A_i 1\{k = \ell\} \right) + \sum_{\ell \neq k_0} \beta_\ell \left(E_{z,i} 1\{k = \ell\} \right) \\
+ \sum_{\ell \neq k_0} \theta_\ell \left(A_i 1\{k = \ell\} \right) + u_{i,k},
\end{aligned}
\tag{5}
$$

where α_i are country fixed effects, δ_k are day fixed effects, and the omitted baseline period is $k_0 = -1$. The coefficient γ_k measures how the exposure slope with respect to $E_{z,i}$ varies with adoption at event day k, relative to the baseline. I estimate equation (5) by fixed effects panel OLS and cluster standard errors at the country level. Because A_i is centred at its sample median, β_k is the exposure slope for a country with median adoption and θ_k is the adoption slope for a country with average exposure. As in Section 4.3, I also report a summary specification that averages the triple interaction over the two-day post window:

$$
Y_{i,k} = \alpha_i + \delta_k + \gamma^{\text{post}}(E_{z,i} A_i \text{Post}_k) + \beta^{\text{post}}(E_{z,i} \text{Post}_k) + \theta^{\text{post}}(A_i \text{Post}_k) + u_{i,k}, \tag{6}
$$

where $\text{Post}_k = 1\{k \in [0, 1]\}$. H3 predicts that crypto adoption amplifies adverse exposure effects. Under H3, higher adoption strengthens the negative exposure slope after the shock. This implies $\gamma_k < 0$ for $k \geq 0$ and $\gamma^{\text{post}} < 0$.

Table 5: Dynamic DDD with Fixed Effects: Post-Window Average Triple Interaction

	Panel A: Store-of-Value	**Panel B: Bank Fragility**
$E_z \times A \times$ Post	−19.19 (74.07)	94.79 (189.97)
$E_z \times$ Post	4.45 (27.47)	−11.37 (52.75)
$A \times$ Post	−7.81 (32.23)	14.44 (54.64)
Pretrend Wald p	0.003	0.500
Observations (country–day)	608	498
Entities (countries)	55	45
Time periods (dates)	19	16
Within R^2	0.0006	0.0012

Notes: This table reports post-event average triple-difference coefficients from a dynamic event-study regression with country and day fixed effects. The dependent variable is the daily abnormal bank equity return in basis points. E_z denotes the standardised exposure composite ($E_{\text{sov},z}$ in Panel A and $E_{\text{frag},z}$ in Panel B), and A_i is the median-centred adoption percentile $A_{pc,i}$. The coefficient "$E_z \times A \times$ Post" is the post-window average (over event days $k \in [0, 1]$) of the triple interaction $E_{z,i} A_i \mathbf{1}\{K_t = k\}$ relative to the pre-event baseline period $k_0 = -1$; the lower-order post-event interactions "$E_z \times$ Post" and "$A \times$ Post" are reported for completeness. Standard errors are clustered by country and reported in parentheses. "Pretrend Wald p (all $k < 0$)" is the p-value from a joint test that all pre-event coefficients in the corresponding DDD specification are equal to zero. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

The store-of-value panel contains 608 country–day observations from 55 countries and 19 event days. The fragility panel contains 498 observations from 45 countries and 16 event days. These samples match those used in Section 4.3, so identification again comes from within-country movements in returns around the event that differ across the joint distribution of exposure and adoption.

Average post-event amplification

Table 5 reports the average post-event triple-difference coefficient γ^{post} from equation (6). For the store-of-value specification, the estimate on $E_z \times A \times$ Post is -19.19 bps (SE = 74.07). For the bank-fragility specification, the corresponding coefficient is 94.79 bps (SE = 189.97). Neither estimate is statistically different from zero at the 10% level, and both are small relative to their standard errors. The lower-order post-event interactions on $E_z \times$ Post and $A \times$ Post are likewise imprecisely estimated and not statistically significant (Table 5). On the two-day horizon $k \in [0, 1]$, the panel averages therefore do not support H3: the data do not show that higher adoption systematically strengthens the relationship between exposure and abnormal returns in either specification.

Pretrend diagnostics based on the triple interaction qualify this conclusion for the store-of-value case. For store-of-value exposure, the joint Wald test that all pre-event γ_k are zero yields a p-value of 0.003, which rejects the null at the 1% level. For bank fragility, the corresponding p-value is 0.50, and I do not reject the null of parallel pretrends in the triple interaction (Table 5).

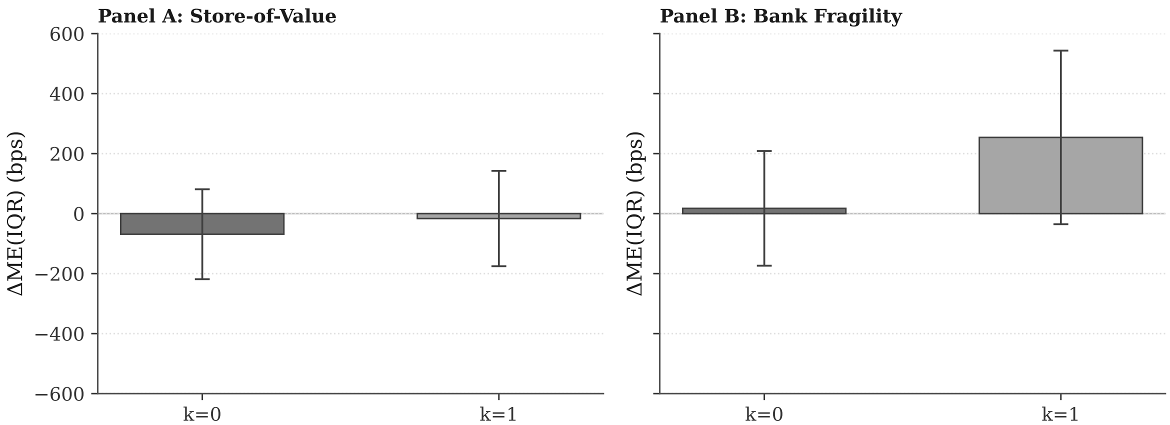

Figure 4: Adoption Amplification of Exposure Effects (Interquartile Shift).
Notes: Bars plot $\Delta ME(\text{IQR})$, the change in the marginal effect of exposure on abnormal bank returns when adoption A_{pc} rises from the 25th to the 75th percentile. $\Delta ME(\text{IQR})$ is computed from the dynamic triple-difference estimates in equation (5) and reported for $k = 0$ and $k = 1$. Whiskers denote 95% confidence intervals derived from country-clustered standard errors. Results are shown separately for $E_{\text{sov},z}$ and $E_{\text{frag},z}$.

Figure 4 plots the change in the exposure effect when adoption moves from the 25th to the 75th percentile, $\Delta ME(\text{IQR})$, for event days $k = 0$ and $k = 1$, and Table A3 reports the underlying event-time coefficients γ_k. In the store-of-value specification, the post-event γ_k are imprecise: at the announcement day and the day after, the estimates are on the order of -100 to 0 bps with standard errors of similar magnitude, and none of the post-event coefficients are statistically significant at the 10% level (Figure 4; Table A3). By contrast, one pre-event coefficient is more pronounced: at $k = -2$, the store-of-value triple interaction is -201.3 bps (SE = 94.63), which is statistically significant at the 5% level. Together with the pretrend Wald test, this indicates that countries combining weak monetary conditions and high adoption already experienced relatively lower abnormal returns before the GENIUS Act.

In the bank-fragility specification, the pre-event γ_k are noisy and jointly insignificant (Appendix Table A3). The post-event coefficients are generally small relative to their standard errors, with one notable exception: at $k = 1$, the triple interaction is 504.5 bps (SE = 293.24), which is marginally significant at the 10% level but associated with a wide confidence interval that spans economically meaningful losses as well as large gains. In Figure 4, this appears as a large positive $\Delta ME(\text{IQR})$ for fragility at $k = 1$, whereas the corresponding bars for store-of-value are close to zero with confidence intervals that cover moderate negative and positive changes. Overall, the event-time profile and the $\Delta ME(\text{IQR})$ plot highlight substantial statistical uncertainty around the triple interaction effects (Figure 4; Table A3).

Interpretation

The empirical analysis therefore does not provide evidence in support of H3, and RQ3 remains unsubstantiated. Conditional on country and day fixed effects, there is no consistent evidence that higher crypto adoption amplifies the effect of weak monetary conditions or fragile banking systems on short-run bank equity responses to the GENIUS Act. If such amplification exists, it is either small in magnitude relative to the noise in daily returns, or it operates over a horizon longer than the event window considered here (MacKinlay, 1997). Taken together with the results in Sections 4.2 and 4.3, the evidence suggests that market participants do not price the GENIUS Act primarily through an interaction of pre-existing monetary or bank fragility with crypto adoption. This implies that any adoption-threshold channel is not yet operating at a scale visible in short-horizon bank equities. Abnormal returns do not react as if the GENIUS Act shock delivers new, price-relevant information about deposit substitution. Instead, the pricing pattern is consistent with two concrete market readings highlighted in the literature: investors either expect GENIUS to integrate stablecoins as supervised, fully-reserved payment instruments that limit near-term competition with deposits, or they wait for implementing rules—covering reserve verification, issuer constraints, and redemption enforcement—to determine whether stablecoins become deposit-like at scale. Under either reading, the marginal news does not warrant an immediate revision to expected bank cash flows or franchise values, so equity prices show no systematic short-run response.

4.5 Robustness

The exposure estimates are imprecise, and the point estimates are small. A natural concern is that these weak exposure effects reflect particular modelling choices, limited power in a small cross-section with noisy returns, or a handful of influential countries, rather than the underlying relationship between exposures and returns. The robustness analysis has two roles. First, it evaluates whether alternative and equally defensible implementations of the event-study design, return construction and sample compositions would overturn the main conclusion that exposure effects are small and imprecise. Second, it quantifies the sampling uncertainty around the baseline estimates and examines whether the results are sensitive to influential countries or to specific parts of the cross-section, such as EMDEs, where adoption tends to be higher.

I focus on a targeted set of robustness checks. Each test addresses a concrete empirical concern that arises from the design in Sections 5.1–5.4 and from standard issues in event-study econometrics (MacKinlay, 1997; Wooldridge, 2010). I vary the abnormal return model by replacing simple market-adjusted returns with β-adjusted returns estimated at the bank level, which mitigates concerns about benchmark mis-specification. I change the aggregation scheme from equal-weighted to value-weighted country returns, which allows large banks to receive more weight in the cross-section. I extend the event window for cumulative abnormal returns, which tests whether the effects materialise over longer horizons than the two-day window used in the baseline. I trim countries with extreme exposure and return realisations, which addresses the influence of heavy tails in equity returns. I also study EMDE heterogeneity directly in the CAR cross-section, quantify minimum detectable effect sizes, and implement jackknife leave-one-out tests to assess whether the baseline estimates depend on any single country. Together, these robustness checks address issues of power, measurement error, outliers and heterogeneity that can drive statistically insignificant results in small cross-sections (Angrist & Pischke, 2009; MacKinnon & White, 1985; Wooldridge, 2010).

Cross-Sectional Robustness

Table 6: Robustness of Post-Window Cross-Section: CAR(0–1) on Exposure

	(1) Baseline	(2) β-adjusted	(3) Value-weighted	(4) CAR(0–10)	(5) CAR(0–30)	(6) Trimmed sample
Panel A: Store-of-Value						
Exposure β	−11.3 (12.8)	−11.1 (13.7)	−3.4 (18.1)	−42.0 (67.5)	−87.4 (150.4)	−31.6 (72.4)
Observations N	55	55	55	55	53	49
R^2	0.015	0.017	0.004	0.013	0.028	0.018
Adj. R^2	−0.003	−0.001	−0.015	−0.005	0.009	−0.003
Panel B: Bank Fragility						
Exposure β	45.5 (44.3)	38.6 (44.5)	25.5 (25.3)	−17.9 (122.7)	79.8 (295.5)	25.5 (29.1)
Observations N	45	45	45	45	44	40
R^2	0.059	0.053	0.058	0.001	0.006	0.009
Adj. R^2	0.037	0.031	0.036	−0.023	−0.017	−0.017

Notes: This table reports robustness checks for the post-window cross-sectional regression of the cumulative abnormal return CAR(0–1) on the standardised exposure composites. Column (1) reproduces the baseline specification reported in Table 3 with equally weighted country-level event-study returns. Column (2) uses abnormal returns that are β-adjusted with respect to the local equity index. Column (3) replaces equal-weighted country-day returns with value-weighted returns based on bank-level trading volume. Columns (4) and (5) extend the event window for the dependent variable to CAR(0–10) and CAR(0–30), respectively. Column (6) trims countries with extreme dispersion in daily abnormal returns around the event. The dependent variable and coefficients are measured in basis points. Heteroskedasticity-robust (HC3) standard errors are reported in parentheses. Intercepts are estimated but not reported. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

I begin by stress testing the cross-sectional CAR specification in equation (2), which provides the most transparent reduced form for RQ2 and underpins the interpretation of the panel results. Table 6 reports estimates of equation (2) under alternative constructions of the abnormal return process and the cumulative event window.

Table 6 reports estimates of equation (2) under alternative constructions of the abnormal-return process and the cumulative event window. Panel A covers store-of-value exposure; Panel B covers bank fragility. Column (1) reproduces the baseline equal weighted CAR(0–1) regression from Table 3. Columns (2) and (3) vary the construction of abnormal returns. Column (2) replaces simple market adjusted returns with bank level beta adjusted returns to check whether the results are sensitive to the benchmark. Abnormal returns are the residuals from a pre event regression of bank returns on the domestic equity index, so that differences in banks' systematic risk are removed before relating returns to the exposure indices. Column (3) retains the short event window but aggregates daily abnormal returns using weights proportional to each bank's 30-day average daily value traded. This construction gives larger and more liquid banks greater influence on the country-level cumulative abnormal return. Columns (4) and (5) vary the event horizon by extending the cumulative return window to CAR(0–10) and CAR(0–30) while maintaining equal weights. Column (6) focuses on the influence of outliers by trimming countries with extreme joint realisations of exposure and CAR. This test asks whether the exposure–return slope is similar once the most extreme combinations of exposure and CAR are excluded, or whether the baseline result is driven by a small number of tail observations.

The store-of-value results in Panel A are stable across specifications and remain statistically insignificant. The baseline coefficient in column (1) is -11.3 bps, and the β-adjusted specification in column (2) yields a very similar estimate of -11.1 bps. Value weighting in column (3) moves the point estimate closer to zero, to -3.4 bps. Extending the event window to CAR010 and CAR030 in columns (4) and (5) produces more negative but increasingly noisy estimates, while trimming extremes in column (6) gives -31.6 bps. In every case the confidence interval for the exposure slope includes zero and spans moderate to potentially sizeable declines and gains. The R^2values range from 0.004 to 0.028 and the adjusted R^2 is close to zero or negative, confirming that the store-of-value index explains only a small fraction of the cross-country dispersion in cumulative abnormal returns (Table 6).

The fragility results in Panel B are somewhat more variable in sign but display the same pattern of statistical imprecision. The baseline coefficient in column (1) is 45.5 bps. The β-adjusted specification in column (2) gives 38.6 bps, and value weighting in column (3) reduces the point estimate to 25.5 bps. For the longer event windows, the estimates become very noisy: the CAR010 and CAR030 slopes in columns (4) and (5) have wide confidence intervals that encompass both negative and positive effects of economically meaningful size. The trimmed sample in column (6) yields 25.5 bps. Across all fragility specifications, the 95% confidence intervals contain zero, and the R^2 and adjusted R^2 remain low and similar to the baseline regression (Table 6).

Econometrically, Table 6 addresses several potential concerns about the baseline cross-section. The β-adjusted specifications respond to the possibility that simple market-adjusted returns may leave unmodelled systematic risk in the disturbance term, which could bias the exposure slope if exposures correlate with betas (MacKinlay, 1997). In practice the β-adjusted estimates are nearly identical to the baseline for store-of-value and only modestly smaller for fragility, which indicates that benchmark mis-specification is unlikely to explain the null results. Value-weighting shifts attention to the equity performance of large banks, which matter more for aggregate financial stability and for international investors. The results show that giving more weight to large banks does not uncover stronger or more negative exposure effects. Extending the event window tests whether markets incorporate the implications of the GENIUS Act more slowly than a two-day window can capture. Although the point estimates for longer horizons become more negative for store-of-value, the associated standard errors increase sharply, which reflects the low signal-to-noise ratio in multi-day bank returns. Trimming extremes reduces the influence of countries with very large CAR or exposure values. The trimmed estimates do not differ systematically from the untrimmed ones, which suggests that the baseline results are not driven by a small number of outliers.

The pattern in Table 6 is consistent with the broader econometric constraints of this setting. The cross-section contains at most 55 countries, and only 45 for the fragility regressions. Sampling variability is therefore substantial and standard errors remain large even in simple one-regressor models. Measurement error in the composite exposure indices is likely, because they combine annual macroeconomic and supervisory indicators that are themselves imperfect measures of underlying monetary and banking conditions. Under classical measurement error, this noise attenuates the estimated slopes toward zero and reduces the probability of rejecting the null hypothesis even when true effects exist (Wooldridge, 2010). Bank equity returns are volatile and respond to many unobserved country-specific and global shocks that are not captured by the composite exposure indices, which further lowers the signal-to-noise ratio in the CAR cross-section (MacKinlay, 1997). Given these features, it is not surprising that even relatively large shifts in model specification, weighting and window length do not yield precise estimates of exposure effects.

I interpret Table 6 as showing that the main conclusion from Section 4.2 is robust to a wide range of plausible cross-sectional choices. There is no evidence that alternative abnormal return models, weighting schemes, event windows or trimming rules reveal a strong and systematic relationship between the composite exposure indices and short-horizon cumulative abnormal bank returns after the GENIUS Act shock.

Jackknife and Minimum Detectable Effects

Table A4 summarises two complementary diagnostics for the post-window cross-sectional exposure effect in equation (2): minimum detectable effects and leave-one-country-out jackknife slopes. For store-of-value exposure, the baseline estimate is -11.3 bps with a 95% confidence interval of roughly $[-36, 14]$ bps and a minimum detectable effect (two standard errors) of about 25.6 bps. The jackknife slopes range from -23.3to -9.1 bps and remain negative in every replication. For bank fragility, the baseline estimate is 45.5 bps with a 95% confidence interval of roughly $[-41, 132]$ bps and a minimum detectable effect of about 88.6 bps; the jackknife range is 21.6–68.5 bps and remains positive across replications (Table A4). These diagnostics indicate that the cross-sectional coefficients are internally stable to omitting individual countries, but that the sample only has power to rule out relatively large exposure effects.

EMDE vs. Advanced Economies in CAR(0,1)

Table A5 examines whether the post-window cross-sectional exposure effect in equation (2) differs between advanced economies and EMDEs. In the store-of-value specification, the advanced-economy slope is positive but very imprecisely estimated, and the EMDE slope is small and close to zero. The explanatory power is low in both subsamples. In the fragility specification, the advanced and EMDE slopes are again imprecise, and the associated confidence intervals include economically modest negative and positive effects. None of the subgroup coefficients is statistically different from zero at the 10% level (Table A4). The split-sample regressions therefore do not reveal a robust pattern of EMDE heterogeneity in the short-horizon CAR response.

β-Adjusted Panel Specifications

Table A6 evaluates whether adjusting abnormal returns for bank-level market betas changes the panel results for equations (4) and (6). For the post-window DiD specification summarising equation (4), the β-adjusted exposure coefficients on $E_z \times$ Postare -3.9 bps for store-of-value exposure and 13.0 bps for bank fragility. For the triple-difference specification associated with equation (6), the β-adjusted triple interactions $E_z \times A \times$ Post are -25.1 bps in the store-of-value panel and 127.8 bps in the fragility panel. In all cases the coefficients are small relative to their standard errors, not statistically significant at conventional levels, and associated with within-R^2 values close to zero (Table A6). The β-adjusted panel results therefore confirm that the main DiD and triple-difference conclusions do not hinge on using simple market-adjusted abnormal returns.

Summary of Robustness Results

The robustness exercises in this section point to a consistent conclusion. Across a wide range of plausible modelling choices for the CAR cross-section in equation (2) and the panel specifications in equations (4) and (6), the exposure indices are not associated with statistically significant effects on bank equity returns around the GENIUS Act shock. Adjusting the abnormal-return model, changing the weighting scheme, extending the event window, trimming outliers, splitting the sample by EMDE status, and re-estimating the models with β-adjusted returns all leave the point estimates small relative to their standard errors. The jackknife and minimum detectable effect diagnostics suggest that the estimates are internally stable, but that the sample only has power to rule out relatively large exposure effects in short-horizon returns.

Combined with the adoption evidence in Section 4.1 and the main results in Sections 4.2–5.4, the robustness analysis supports the interpretation that, on the horizons considered here, market participants do not appear to price the GENIUS Act through the composite store-of-value and fragility exposures. If they do, the effect is too small to be detected in this sample given our measurement approach.

4.6 Limitations

Several features of the data and the empirical design limit how far the results can be generalised. These limitations do not overturn the findings, but they constrain the set of claims that the analysis can support.

The country sample is small and selective. The store-of-value specifications include at most 55 countries and the fragility specifications at most 45 countries. Only countries with reliable exposure data, crypto adoption measures and sufficiently liquid listed banks enter the event–study sample. This selects toward more financially developed EMDEs and advanced economies with functioning equity markets and supervisory reporting, and excludes many small or fragile jurisdictions. As a result, statistical power is limited and external validity is restricted. The minimum detectable effects for CAR(0–1) are sizable in basis-point terms, so the design can rule out only relatively large short-run exposure effects. Smaller negative or positive effects remain observationally indistinguishable from zero in this sample (Angrist & Pischke, 2009; Wooldridge, 2010).

The key regressors are composite indices and cross-country percentiles that are likely measured with error. The store-of-value and fragility indices combine annual macroeconomic and supervisory indicators. These inputs are themselves noisy proxies for underlying monetary stress and bank health and they are measured at an annual frequency rather than exactly at the event date. The crypto adoption measure is a within-sample percentile constructed from on-chain activity, exchange data and related indicators and is subject to data coverage and modelling choices. Importantly, the Chainalysis index captures overall crypto adoption and is not stablecoin-specific; if stablecoin usage diverges from broader crypto activity across countries, this introduces additional measurement error in my adoption proxy. Under a classical measurement-error framework, noise in these regressors attenuates estimated slopes toward zero and lowers the probability of detecting true effects, especially in small samples (Wooldridge, 2010). The weak exposure and amplification estimates may therefore partly reflect imperfect measurement of monetary conditions, bank fragility and adoption rather than the complete absence of underlying relationships.

The mapping from the prediction-market timestamp to local trading days introduces additional timing uncertainty. The identification of event day 0 relies on converting the intraday shock into local exchange time and defining windows that straddle the information arrival. This approach is standard in international event studies, but closing times, trading halts and market microstructure can still cause the effective price reaction to spill across days (MacKinlay, 1997). The use of a two-day [0,1] window reduces this concern relative to a one-day window, but it cannot fully align the timing of all markets. This timing imprecision may further dilute measured exposure effects.

The outcome variable is daily abnormal bank-equity returns aggregated to the country level. Equity returns respond to a broad set of observable and unobservable shocks, including risk-premia movements, global risk sentiment and idiosyncratic news, which reduces the signal-to-noise ratio in event-study regressions (MacKinlay, 1997). The construction of abnormal returns using domestic equity indices, and in robustness checks beta-adjusted residuals, mitigates benchmark mis-specification but may not remove all systematic components. Aggregating to country-level abnormal returns helps to average out bank-specific noise but also hides within-country heterogeneity in how individual banks respond to the shock. The analysis therefore cannot speak to distributional effects across banks, nor to other risk dimensions such as funding costs, deposit flows, lending volumes or default risk.

The analysis centres on a single regulatory shock and on short event windows. The GENIUS Act prediction-market increase is treated as an exogenous information shock for global bank equities. This places weight on the assumption that the change in predicted passage is not itself driven by bank-specific news and that there are no other major regulatory or macroeconomic announcements that systematically coincide with the event date. Short windows such as [0,1] are designed to minimise confounding news, yet they cannot fully rule out overlapping information arrivals across many countries and time zones (MacKinlay, 1997). Moreover, short horizons primarily capture immediate repricing of expected cash flows and discount rates. They are less informative about medium-run adjustments that may operate through gradual deposit substitution, changes in funding structures, or shifts in business models.

The interpretation of the event also depends on the size of the news component. In the prediction-market data, the implied probability of passage is already high in the days leading up to the event timestamp, so the event captures a move from high to very high likelihood rather than from near-zero to near-certain passage (Figure A1). In that case, theory implies that the incremental price effect is proportional to the change in probability, not to the full impact of the regulation. If most of the expected effect of the GENIUS Act is priced earlier, the remaining surprise on the event date is small, and any associated exposure effects are correspondingly limited in magnitude. The estimates in this study are therefore best interpreted as measuring the response of bank-equity returns to the final revision in expected passage probabilities, rather than to the introduction of the regulation itself. This interpretation is conditional on the event date capturing a non-trivial information shock for equity market participants who price the banks in my sample. Moreover, short horizons primarily capture immediate repricing of expected cash flows and discount rates. They are less informative about medium-run adjustments that may operate through gradual deposit substitution, changes in funding structures, or shifts in business models. If the main consequences of the GENIUS Act materialise over longer horizons, the short event windows used here are likely to understate the total impact on bank valuations.

Inference uses heteroskedasticity-robust and cluster-robust standard errors in a setting with a modest number of clusters. The cross-sectional regressions report HC3 standard errors to address heteroskedasticity and influential observations (MacKinnon & White, 1985). The panel regressions cluster at the country level to account for serial correlation and heteroskedasticity within countries (Angrist & Pischke, 2009). With 45 to 55 countries and 16 to 19 time periods, cluster-robust variance estimators may have non-negligible finite-sample distortions and the analysis does not implement refinements such as wild bootstrap procedures (Cameron & Miller, 2015). Reported p-values and confidence intervals should therefore be interpreted as approximate rather than exact.

The empirical models are deliberately parsimonious. The cross-sectional regressions relate cumulative abnormal returns linearly to a single exposure composite. The panel specifications introduce event-time and adoption interactions but maintain linearity in the indices. Heterogeneity is captured only through EMDE status and the adoption percentile. The models do not allow for non-linear effects, thresholds in exposure or adoption, or interactions with bank-level characteristics such as size, funding structure or capitalisation. If the impact of the GENIUS Act depends in a non-linear way on exposure or adoption, or is concentrated in particular types of banks or countries, the linear average effects estimated here may understate those patterns.

Finally, the exposure measures do not incorporate bank-specific links to crypto markets or more granular regulatory channels. The composite indices reflect macroeconomic conditions and supervisory metrics at the country level. They do not capture heterogeneity in banks' direct involvement in crypto-related activities, their stablecoin customer base, or institution-specific expectations about future regulation. If the main transmission of the GENIUS Act to bank valuations operates through these micro channels, rather than through broad macro-financial conditions, the current design may miss part of the relevant variation. The results should therefore be interpreted as evidence about how short-run equity returns relate to aggregate monetary and banking conditions and crypto adoption, rather than as a full assessment of all channels through which the GENIUS Act may affect bank risk and profitability.

Taken together, these limitations suggest that the analysis is well suited to ruling out large average short-run exposure effects in bank-equity returns, given the available data and identification strategy. It is less informative about smaller effects, longer horizons and richer forms of heterogeneity, which motivates the need for complementary evidence in future work.

4.7 Implications for Future Research

The empirical results suggest several directions for future work on stablecoins, bank disintermediation and regulation.

First, the evidence on RQ1 indicates that cross-country crypto adoption is more closely related to store-of-value weakness than to bank fragility, particularly in EMDEs. Future research could move beyond country-level indices and examine micro data on households and firms. Combining survey evidence, transaction-level payment data and on-chain flows with macro indicators would allow researchers to distinguish more sharply between adoption as an inflation hedge, as a payment technology, or as a speculative asset. This would help to quantify how much of the observed association between adoption and weak money reflects genuine currency substitution, and how much reflects other motives.

Second, the weak and imprecise exposure effects for RQ2 and RQ3 motivate designs that follow balance-sheet and funding variables over longer horizons. One natural extension is to link the exposure indices used here to bank-level panel data on deposits, funding costs, loan growth and asset composition. With a sufficiently long time series, researchers could test whether stablecoin growth and regulatory developments are associated with persistent changes in banks' liability structures and credit supply, using DiD or local-projection methods. Such analyses would speak more directly to the deposit-disintermediation and credit-supply channels that motivate much of the theoretical and policy literature.

Third, the focus on a single regulatory event suggests that a broader event set would be valuable. The GENIUS Act is an important legal development, but it represents only one point on a path of policy announcements, legislative proposals and supervisory actions. Future work could construct a panel of stablecoin-relevant events across major jurisdictions and estimate pooled event-study and panel regressions. This would increase statistical power, permit comparisons across different types of regulatory shocks, and provide a basis for formally testing whether markets respond more strongly to hard legislation, to enforcement actions, or to supervisory guidance.

Fourth, the exposure measures in this thesis are defined at the country level and do not incorporate bank-specific links to crypto markets. The composite exposure indices and adoption percentiles are transparent and comparable across countries, but they inevitably blur within-country and within-bank variation. Future studies could separate stablecoin-specific activity from broader crypto use, distinguish retail from institutional adoption, and incorporate bank-level indicators of direct involvement in crypto markets or reliance on cross-border retail funding. Methodologically, non-linear specifications, threshold models and interactions with bank characteristics such as size, funding structure and capitalisation would help to identify whether stablecoin risks only become material beyond certain adoption or exposure levels. This is particularly relevant for advanced economies, where adoption is currently lower but could grow quickly if BigTech-issued coins emerge as mainstream payment instruments.

Finally, the use of prediction-market data to time the information shock points to a broader methodological agenda. Prediction markets increasingly provide high-frequency estimates of the probability of policy events. Future work could exploit this feature more fully, for example by modelling the joint dynamics of prediction-market prices and bank equities during legislative processes, and by distinguishing between the pricing of incremental probability revisions and the pricing of implementation details that follow after a law is passed. This would refine identification of policy shocks and could be applied to other regulatory settings beyond stablecoins.

5 Conclusion

This thesis examines how the rise of dollar-pegged stablecoins interacts with traditional banking systems through the lens of a major regulatory development, the U.S. GENIUS Act. The motivation comes from concerns that credible, widely usable stablecoins may facilitate digital dollarisation and disintermediate banks, especially where domestic money is weak or banking systems are fragile. Within this context, the analysis addresses three research questions: how crypto adoption relates to weak monetary and banking conditions across countries (RQ1), whether bank equity abnormal returns around the GENIUS Act shock vary systematically with those conditions (RQ2), and whether higher crypto adoption amplifies any such exposure effects (RQ3).

The evidence for RQ1 shows that crypto adoption tends to be higher in EMDEs than in advanced economies and is positively associated with weaker monetary conditions. By contrast, crypto adoption displays no strong or robust association with the weaker banking conditions. This is consistent with the view that monetary instability, rather than weak bank capital and liquidity, is the primary cross-country correlate of higher crypto adoption. This also suggests that the countries most exposed to potential digital dollarisation are those that combine weak domestic money with already high levels of crypto use. This pattern is broadly in line with the emerging empirical literature that highlights stablecoin use in vulnerable monetary environments.

For RQ2, the cross-sectional and panel event-study results do not indicate statistically significant exposure effects in bank-equity returns around the GENIUS Act shock. Robustness checks that vary the construction of abnormal returns, the weighting scheme, the event window and the sample do not overturn these results. For RQ3, the triple-difference specifications do not provide consistent evidence that higher crypto adoption amplifies exposure effects on bank returns in the short-run period following the Act.

Taken together, the main findings suggest that, as of the GENIUS Act event, the estimates do not provide clear evidence of large, systematic exposure-related equity losses. Within the limits of this design, there is no clear sign that equity-market participants treated the Act's final passage as a major, immediate threat to bank franchise values via deposit substitution, even in countries with high adoption and weak monetary conditions. This interpretation is conditional on the event date capturing a non-trivial information shock. This pattern is not inconsistent with the current scale and use of stablecoins, which remain small relative to global bank balance sheets and are still concentrated in trading and decentralised finance activity. It is also plausible that investors expect the Act to channel stablecoins into a more regulated, complementary role, or that domestic policy responses will limit destabilising outflows from banks in vulnerable jurisdictions.

At the same time, the null results do not imply that the underlying risks emphasised in the theoretical and policy literature are irrelevant. The prediction-market path indicates that the event studied here corresponds to a revision from a high to a very high probability of passage, not from near zero to near certain passage. In that setting, standard asset-pricing logic implies that the price response is proportional to the marginal change in expected outcomes, not to the full effect of the regulation. If most of the anticipated impact of the GENIUS Act was capitalised earlier in the legislative process, or if the main consequences arise gradually through changes in funding structures and business models, then the two-day equity response around the final revision will be limited by design. The estimates in this thesis are therefore interpreted as measuring the response of bank-equity returns to the final revision in expected passage probabilities at short horizons, rather than to the full long-run impact of the regulation itself. Under this interpretation, the null results indicate that large, immediate marginal effects are not visible in bank equities at this stage, but they do not rule out more gradual or nonlinear effects as stablecoins scale.

Within this interpretation, the thesis makes three contributions. I provide a baseline cross-country characterisation of the relationship between crypto adoption, monetary weakness and bank fragility, clarifying where digital dollarisation pressures are strongest. I introduce a novel regulatory setting that uses prediction-market data to time a global stablecoin shock and applies event-study and

DiD modelling to bank equities in a broad international sample. Finally, I provide a market-based benchmark for the current phase of the stablecoin–bank nexus. At current scale, and given the limitations of this design, investors do not appear to price this type of stablecoin-specific regulation as an immediate, first-order source of deposit-substitution or franchise-value risk for banks.

Looking forward, the message of this study is conditional and incremental rather than definitive. The results suggest that, in the environment captured here, the stablecoin–bank nexus is still in an early phase from the perspective of listed banks' valuations. The central policy issue is therefore not whether stablecoins can matter for banks in principle, but when, and through which channels, they might start to do so in practice. If, stablecoins become deeply embedded in everyday payments and savings, the same mechanisms that underlie classic dollarisation and shadow banking are likely to become important. In that scenario, shifts from insured deposits into private digital dollars could affect the cost and availability of credit, the resilience of domestic banking systems and, ultimately, the stability of households' access to safe money and payments.

The framework and evidence in this thesis provide a starting point for monitoring that evolution. As new regulatory events unfold, as adoption continues to rise in EMDEs and possibly in advanced economies, and as alternative architectures such as tokenised deposits and central bank digital currencies develop, researchers could re-apply and extend this approach. Doing so will help clarify when, and through which channels, private digital dollars begin to generate the material disintermediation and financial-stability effects that current theoretical and policy debates anticipate. This is important for academic understanding of how money, banking and private digital currencies interact. It also matters for the design of regulatory regimes that support innovation in digital finance while safeguarding bank-based intermediation and the stability of payment and savings arrangements that households and firms rely on.

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Appendix

Table A1: Country Composition of Event-Study Samples

Country	ISO3	Group	$N_{\text{liquid banks}}$	E_z	$\text{CAR}_{[0,1]}$ (bps)	$A_{\text{pc}}^{\text{SoV}}$
Panel A: Store-of-Value Event-Study Regression Sub-Sample						
Austria	AUT	Advanced	7	-0.249599	102.825470	0.013333
Belgium	BEL	Advanced	2	-0.238897	-77.626554	0.053333
Czechia	CZE	Advanced	2	-0.160031	9.957990	0.166667
Denmark	DNK	Advanced	16	-0.326862	-38.777828	-0.180000
Estonia	EST	Advanced	2	-0.219268	-49.537362	-0.086667
Finland	FIN	Advanced	5	-0.321034	57.719835	-0.046667
France	FRA	Advanced	11	-0.298475	47.902641	0.360000
Germany	DEU	Advanced	5	-0.285072	57.133515	0.366667
Greece	GRC	Advanced	7	-0.259825	89.119488	0.100000
Hong Kong SAR, China	HKG	Advanced	6	-0.318074	-280.580261	0.313333
Iceland	ISL	Advanced	2	-0.094843	189.759919	-0.440000
Ireland	IRL	Advanced	4	-0.292519	-54.110819	-0.173333
Israel	ISR	Advanced	8	-0.218185	-64.717252	0.040000
Italy	ITA	Advanced	15	-0.351401	-16.397003	0.260000
Korea, Rep.	KOR	Advanced	12	-0.170117	-33.838002	0.380000
Malta	MLT	Advanced	2	-0.316604	97.485360	-0.393333
Netherlands	NLD	Advanced	1	-0.228275	87.179477	0.293333
New Zealand	NZL	Advanced	1	-0.211690	-2.635511	-0.126667
Norway	NOR	Advanced	22	-0.193656	-74.608920	-0.153333
Portugal	PRT	Advanced	1	-0.276762	138.929753	0.173333
Slovenia	SVN	Advanced	1	-0.300214	88.077013	-0.140000
Spain	ESP	Advanced	6	-0.258123	-2.295865	0.340000
Switzerland	CHE	Advanced	16	-0.394253	-22.169123	0.140000
United States	USA	Advanced	466	-0.246461	13.521977	0.480000
Argentina	ARG	EMDE	7	6.088224	-22.426080	0.406667
Bangladesh	BGD	EMDE	36	0.360456	21.670743	0.273333
Brazil	BRA	EMDE	5	0.022210	-288.696525	0.440000
Bulgaria	BGR	EMDE	1	-0.274181	235.183110	0.153333
Chile	CHL	EMDE	5	0.127625	-1.783268	0.160000
China	CHN	EMDE	53	-0.349135	-164.127119	0.373333
Colombia	COL	EMDE	4	-0.199363	6.332107	0.266667

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Croatia	HRV	EMDE	3	-0.247825	-31.099304	-0.100000
Egypt, Arab Rep.	EGY	EMDE	11	2.253399	-44.321472	0.213333
Ghana	GHA	EMDE	2	1.782073	-91.724100	0.200000
Hungary	HUN	EMDE	2	-0.119164	-159.456841	0.106667
India	IND	EMDE	46	-0.110211	-86.642829	0.500000
Indonesia	IDN	EMDE	40	-0.186309	-7.031356	0.486667
Kazakhstan	KAZ	EMDE	3	0.129353	186.285956	0.126667
Kuwait	KWT	EMDE	10	-0.253087	0.989226	-0.313333
Malaysia	MYS	EMDE	11	-0.295980	-18.856341	0.193333
Mauritius	MUS	EMDE	2	-0.149841	-4.513061	-0.473333
Mexico	MEX	EMDE	4	-0.078322	-49.407539	0.413333
Morocco	MAR	EMDE	7	-0.394746	43.181063	0.326667
Namibia	NAM	EMDE	2	-0.195063	-19.742733	-0.373333
North Macedonia	MKD	EMDE	2	-0.221568	-6.661431	-0.146667
Pakistan	PAK	EMDE	19	0.241995	22.966797	0.446667
Philippines	PHL	EMDE	11	-0.159152	126.422075	0.453333
Poland	POL	EMDE	12	-0.333786	-57.888958	0.346667
Qatar	QAT	EMDE	9	-0.334032	2.002246	-0.366667
Romania	ROU	EMDE	2	-0.089177	-58.696117	0.073333
Saudi Arabia	SAU	EMDE	11	-0.312138	49.852001	0.233333
South Africa	ZAF	EMDE	5	-0.189229	3.305256	0.306667
Thailand	THA	EMDE	10	-0.294083	120.843306	0.400000
Turkiye	TUR	EMDE	11	3.555108	-70.388808	0.433333
United Arab Emirates	ARE	EMDE	14	-0.313416	45.966829	0.133333
Panel B: Fragility Event-Study Regression Sub-Sample						
Austria	AUT	Advanced	7	-0.320047	102.825470	0.013333
Belgium	BEL	Advanced	2	0.130008	-77.626554	0.053333
Czechia	CZE	Advanced	2	-0.266913	9.957990	0.166667
Denmark	DNK	Advanced	16	-0.438202	-38.777828	-0.180000
Estonia	EST	Advanced	2	-0.199147	-49.537362	-0.086667
Finland	FIN	Advanced	5	-0.060719	57.719835	-0.046667
France	FRA	Advanced	11	0.078867	47.902641	0.360000
Germany	DEU	Advanced	5	-0.104723	57.133515	0.366667
Greece	GRC	Advanced	7	0.092516	89.119488	0.100000
Hong Kong SAR, China	HKG	Advanced	6	-1.290228	-280.580261	0.313333
Iceland	ISL	Advanced	2	-0.172579	189.759919	-0.440000
Ireland	IRL	Advanced	4	-0.543732	-54.110819	-0.173333

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Israel	ISR	Advanced	8	0.182300	-64.717252	0.040000
Italy	ITA	Advanced	15	-0.628539	-16.397003	0.260000
Malta	MLT	Advanced	2	-0.360335	97.485360	-0.393333
Netherlands	NLD	Advanced	1	0.014048	87.179477	0.293333
Norway	NOR	Advanced	22	-0.278623	-74.608920	-0.153333
Portugal	PRT	Advanced	1	-0.105288	138.929753	0.173333
Slovenia	SVN	Advanced	1	-0.119583	88.077013	-0.140000
Spain	ESP	Advanced	6	0.284822	-2.295865	0.340000
United States	USA	Advanced	466	-1.233586	13.521977	0.480000
Argentina	ARG	EMDE	7	-0.963983	-22.426080	0.406667
Bangladesh	BGD	EMDE	36	2.028111	21.670743	0.273333
Brazil	BRA	EMDE	5	-1.439828	-288.696525	0.440000
Bulgaria	BGR	EMDE	1	-0.262444	235.183110	0.153333
China	CHN	EMDE	53	-0.060983	-164.127119	0.373333
Croatia	HRV	EMDE	3	-0.428295	-31.099304	-0.100000
Ghana	GHA	EMDE	2	1.417694	-91.724100	0.200000
Hungary	HUN	EMDE	2	-0.150086	-159.456841	0.106667
India	IND	EMDE	46	-0.043584	-86.642829	0.500000
Indonesia	IDN	EMDE	40	-0.396419	-7.031356	0.486667
Kazakhstan	KAZ	EMDE	3	-0.484921	186.285956	0.126667
Kuwait	KWT	EMDE	10	0.112429	0.989226	-0.313333
Mauritius	MUS	EMDE	2	-0.404947	-4.513061	-0.473333
Mexico	MEX	EMDE	4	-0.565088	-49.407539	0.413333
North Macedonia	MKD	EMDE	2	-0.114666	-6.661431	-0.146667
Pakistan	PAK	EMDE	19	-0.245439	22.966797	0.446667
Philippines	PHL	EMDE	11	0.107209	126.422075	0.453333
Poland	POL	EMDE	12	-0.290369	-57.888958	0.346667
Romania	ROU	EMDE	2	-0.368103	-58.696117	0.073333
Saudi Arabia	SAU	EMDE	11	-0.055281	49.852001	0.233333
South Africa	ZAF	EMDE	5	0.362954	3.305256	0.306667
Thailand	THA	EMDE	10	-0.006146	120.843306	0.400000
Turkiye	TUR	EMDE	11	-0.288364	-70.388808	0.433333
United Arab Emirates	ARE	EMDE	14	0.173645	45.966829	0.133333

Notes: Panel A lists the countries included in the store-of-value (SoV) event-study regressions for equations (2)–(6), where the exposure variable is the standardised SoV index E_z^{SoV}. Panel B lists the subset of these countries for which the bank-fragility exposure index E_z^{Frag} is available and that therefore enter the fragility event-study regressions for equations (2)–(6). $N_{\text{liquid banks}}$ denotes the number of banks with sufficiently liquid equity return data in each country. $\mathrm{CAR}_{[0,1]}$ is the cumulative abnormal bank-equity return over event days 0–1 (in basis points) around the GENIUS Act shock. $A_{\mathrm{pc}}^{\mathrm{SoV}}$ is the median-centred crypto adoption percentile averaged at the country level.

Table A2: Dynamic DiD with Fixed Effects: Event–Time Coefficients by Exposure

Panel A: Store-of-Value

k	$\hat{\beta}_k$	SE	p	Low (95% CI)	High (95% CI)
Baseline $k = -1$ (omitted)					
-5	25.9	24.01	0.281	−21.25	73.09
-4	−24.0	16.40	0.144	−56.21	8.22
-3	1.0	17.04	0.951	−32.44	34.52
-2	−10.2	10.21	0.319	−30.25	9.88
0	4.9	12.57	0.695	−19.76	29.63
1	−25.5	19.63	0.195	−64.07	13.07
2	−13.0	17.30	0.454	−46.96	21.02
3	−17.0	9.50	0.073	−35.69	1.63
4	−17.8	24.58	0.470	−66.08	30.50
5	13.5	12.52	0.280	−11.04	38.14

Pretrend Wald p (all $k < 0$): 0.080 N/entities/time periods: 608 / 55 / 19
Within R^2: 0.0113

Panel B: Bank Fragility

k	$\hat{\beta}_k$	SE	p	Low (95% CI)	High (95% CI)
Baseline $k = -1$ (omitted)					
-5	−32.9	41.50	0.428	−114.49	48.65
-4	14.4	38.84	0.712	−61.98	90.69
-3	−5.0	23.92	0.835	−52.00	42.03
-2	6.1	31.11	0.844	−55.03	67.27
0	−14.9	19.99	0.457	−54.16	24.41
1	45.7	34.68	0.188	−22.44	113.89
2	5.6	43.13	0.896	−79.14	90.42
3	11.4	19.22	0.553	−26.36	49.20
4	6.9	28.67	0.811	−49.49	63.21
5	−11.5	42.04	0.785	−94.10	71.17

Pretrend Wald p (all $k < 0$): 0.880 N/entities/time periods: 498 / 45 / 16
Within R^2: 0.0086

Notes: This table reports event-time coefficients for the interaction between the exposure composite and event-time dummies from a dynamic difference-in-differences regression with country and day fixed effects. The dependent variable is the daily abnormal bank equity return in basis points. Each row shows the coefficient $\hat{\beta}_k$ (bps) for the exposure term at event time k relative to the omitted pre-event period $k_0 = -1$, along with the clustered standard error ("SE"), two-sided p-value ("p"), and 95% confidence interval ("Low" and "High"). Panel A uses the store-of-value exposure $E_{\text{sov},z}$; Panel B uses the bank-fragility exposure $E_{\text{frag},z}$. "Pretrend Wald p (all $k < 0$)" is the p-value from a joint test that all pre-event exposure coefficients are equal to zero. Within R^2, the number of entities, and the number of time periods are taken from the corresponding PanelOLS estimation.

Table A3: Dynamic DDD with Fixed Effects: Event–Time Coefficients for Exposure × Adoption

Panel A: Store-of-Value

k	$\hat{\beta}_k$	SE	p	Low (95% CI)	High (95% CI)
Baseline $k = -1$ (omitted)					
-5	−140.0	241.32	0.562	−614.11	334.14
-4	427.2	314.93	0.176	−191.52	1046.00
-3	−117.2	130.39	0.369	−373.36	138.97
-2	−201.3	94.63	0.034	−387.18	−15.35
0	−136.6	151.93	0.369	−435.05	161.95
1	−32.7	161.05	0.839	−349.13	283.70
2	9.2	252.34	0.971	−486.55	504.99
3	−122.3	116.63	0.295	−351.41	106.88
4	−117.2	185.72	0.528	−482.11	247.65
5	33.2	389.08	0.932	−731.24	797.58

Pretrend Wald p (all $k < 0$): 0.003 N/entities/time periods: 608 / 55 / 19

Within R^2: 0.0268

Panel B: Bank Fragility

k	$\hat{\beta}_k$	SE	p	Low (95% CI)	High (95% CI)
Baseline $k = -1$ (omitted)					
-5	303.4	450.60	0.501	−582.35	1189.2
-4	279.4	350.19	0.426	−409.06	967.8
-3	285.9	183.28	0.120	−74.40	646.2
-2	137.1	310.63	0.659	−473.58	747.7
0	34.7	193.78	0.858	−346.19	415.7
1	504.5	293.24	0.086	−71.93	1081.0
2	128.8	303.56	0.673	−467.95	725.5
3	356.4	244.13	0.145	−123.50	836.3
4	185.4	306.38	0.546	−416.90	787.7
5	562.6	653.28	0.391	−721.63	1846.8

Pretrend Wald p (all $k < 0$): 0.500 N/entities/time periods: 498 / 45 / 16

Within R^2: 0.0277

Notes: This table reports event-time coefficients for the interaction between exposure, adoption, and event-time dummies from a triple-difference regression with country and day fixed effects. The dependent variable is the daily abnormal bank equity return in basis points. Each row shows the coefficient $\hat{\beta}_k$ (bps) for $(E_z \times A)$ at event time k relative to the omitted pre-event period $k_0 = -1$, along with the clustered standard error ("SE"), two-sided p-value ("p"), and 95% confidence interval ("Low" and "High"). Panel A uses the store-of-value exposure $E_{\text{sov},z}$; Panel B uses the bank-fragility exposure $E_{\text{frag},z}$. "Pretrend Wald p (all $k < 0$)" is the p-value from a joint test that all pre-event coefficients in the DDD specification are equal to zero.

Table A4: Jackknife and minimum detectable effect for CAR(0–1)

	β (bps)	SE (bps)	95% CI [lo, hi]	MDE ($|t| = 2$)	Jackknife min	Jackknife max	N
Store-of-Value	−11.3	12.8	[−36.4, 13.8]	25.6	−23.3	−9.1	55
Bank Fragility	45.5	44.3	[−41.3, 132.3]	88.6	21.6	68.5	45

Notes: This table summarises robustness of the post-window cross-sectional exposure effect from Table 3. The dependent variable is the cumulative abnormal return CAR(0–1) in basis points. Columns report the point estimate β, heteroskedasticity-robust (HC3) standard error ("SE"), the associated 95% confidence interval, and the minimum detectable effect ("MDE"), defined as $2 \times$ SE in absolute value (the effect size that would correspond to $|\hat{t}| \approx 2$). "Jackknife min" and "Jackknife max" are the minimum and maximum estimates from leave-one-country-out jackknife replications of the baseline cross-sectional regression. N is the number of countries in the cross-section. Coefficients and intervals are rounded to one decimal place.

Table A5: EMDE vs. Advanced Economies: CAR(0,1)

	Panel A: Store-of-Value	**Panel B: Bank Fragility**
Advanced slope (β_{Adv})	277.5 (379.5)	109.6 (105.3)
EMDE slope (β_{EMDE})	−9.8 (13.2)	30.9 (47.6)
Observations (N), Advanced	24	21
Observations (N), EMDE	31	24
R^2, Advanced	0.038	0.197
R^2, EMDE	0.019	0.035

Notes: This table reports split-sample OLS regressions of the post-window cumulative abnormal return CAR(0–1) on the standardised exposure composite, run separately for advanced economies and EMDEs. The dependent variable is CAR(0–1) in basis points, measured over event days $k \in [0, 1]$. Panel A uses the store-of-value exposure $E_{\text{sov},z}$; Panel B uses the bank-fragility exposure $E_{\text{frag},z}$. "Advanced slope" and "EMDE slope" are the estimated coefficients on E_z within each group. Heteroskedasticity- robust (HC3) standard errors are reported in parentheses. Coefficients are in basis points and rounded to one decimal place. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A6: β-adjusted panel results for Post-Window Cross-Section and Dynamic DiD

	Panel A: Store-of-Value	**Panel B: Bank Fragility**
Post-window exposure slope (β-adjusted)		
$E_z \times$ Post	−3.9 (4.73)	13.0 (17.94)
Post-window triple interaction (β-adjusted)		
$E_z \times A \times$ Post	−25.1 (64.19)	127.8 (184.87)
$E_z \times$ Post	6.7 (24.12)	−24.2 (47.79)
$A \times$ Post	−20.5 (28.71)	13.7 (49.78)
Observations (country–day)	608	498
Entities (countries)	55	45
Time periods (dates)	19	16
Within R^2	0.0004	0.0009
Within R^2	0.0009	0.0019

Notes: This table reports post-event average coefficients from β-adjusted panel specifications. Abnormal returns are adjusted using bank-level market betas with respect to the domestic equity index. The dependent variable is the daily abnormal bank equity return, in basis points. The first block reports the coefficient on the interaction $E_{z,i} \times \text{Post}_t$, where $\text{Post}_t = 1$ for event days $k \in [0, 1]$ and zero otherwise, from a specification with country and day fixed effects. The second block augments this specification by adding the triple interaction $E_{z,i} A_i \times \text{Post}_t$ and the lower-order post-event terms $E_{z,i} \times \text{Post}_t$ and $A_i \times \text{Post}_t$, where A_i is the median-centred adoption percentile $A_{pc,i}$. $E_{\text{sov},z}$ (Panel A) and $E_{\text{frag},z}$ (Panel B) are the standardised store-of-value and fragility exposure indices, respectively. Standard errors are clustered at the country level and reported in parentheses. Coefficients are expressed in basis points and rounded to one decimal place. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

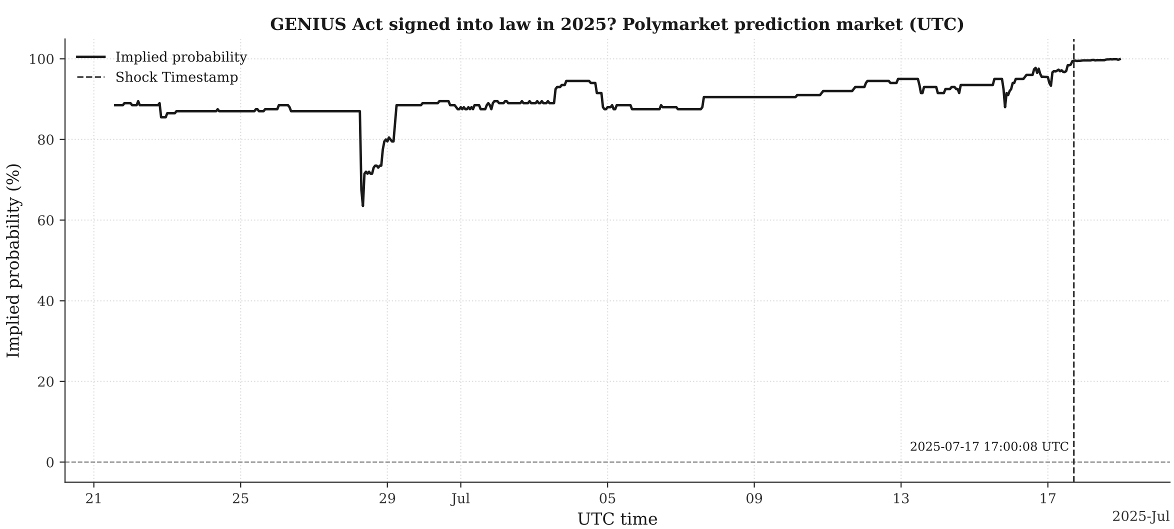

Figure A1: Prediction-Market Probability of the GENIUS Act Signed Into Law in 2025.
Notes: This figure plots the daily implied probability from the Polymarket contract "GENIUS Act signed into law in 2025?". The vertical dashed line marks the sustained-increase shock timestamp used to define the event date in the main analysis. Probabilities are extracted from Polymarket price data and expressed on a 0–1 scale; higher values indicate a greater market-implied likelihood of enactment.