Holding the Bag: Depositor Reactions to a Crypto Shadow Bank Collapse*

IAN APPEL
University of Virginia & ECGI

JILLIAN GRENNAN
Emory University

JOSHUA T. WHITE
Vanderbilt University & ECGI

SEAN WILKOFF
University of Nevada

Abstract

Celsius, a crypto platform functioning as a de facto bank, collapsed. We study how the traits of its global depositor base shaped the run-and-response dynamics. Linking bankruptcy filings to blockchain addresses, demographics, and societal culture, withdrawals reflect formal mechanisms like monitoring as well as informal ones rooted in identity. Depositors from more individualistic societies exited earlier, while those from more hierarchical societies delayed and left stranded balances. Using quasi-experimental variation from withdrawal freezes, users with stranded assets shifted toward higher-risk, concentrated portfolios, consistent with gambling-for-resurrection over flight-to-safety or limited-attention mechanisms. Again, identity-driven forces shape response dynamics, suggesting an underexplored fragility channel in crypto.

Keywords: cryptocurrency, blockchain, digital assets, decentralized finance, DeFi, FinTech, banking, financial intermediation, bankruptcy, financial inclusion, cultural finance, behavioral finance
JEL codes: G18, G32, G24, G28, K22, K24

*Authors: Appel, University of Virginia (appeli@darden.virginia.edu), Grennan, Emory University (jillian.grennan@emory.edu), White, Vanderbilt University (josh.white@vanderbilt.edu) Sean Wilkoff (swilkoff@unr.edu). We thank Ryan Bubb, Yukun Liu (discussant), Andreas Park, Pierre-Charles Pradier (discussant), Donghwa Shin (discussant), and Charlie Wang for helpful comments; and seminar participants at the NYU-SAFE/ESCP BS Law & Finance Conference, GSU-MS AI and FinTech Conference, 14th Fixed Income and Financial Institutions Conference, CBER Webinar, Emory University, University of Tennessee-Knoxville, and University of Nevada-Reno. We thank Louie Labellarte and Gabriel Silva for excellent research assistance. We appreciate research support from UC-Berkeley's Lab for Inclusive FinTech (LIFT). The views expressed herein are our own and do not necessarily reflect the views of any other person, employer, or entity with which we are affiliated.

1. Introduction

The question of why depositors run is central to understanding financial fragility. Seminal work explores how expectations, information, and incentives interact to trigger withdrawals and shape the dynamics of runs (e.g., Diamond and Dybvig, 1983; Chari and Jagannathan, 1988; Goldstein and Pauzner, 2005). Yet our understanding of these events is shaped largely by evidence from chartered banks and other tightly regulated institutions, including money market mutual funds, where deposit insurance, supervisory oversight, and mandated disclosure influence depositor behavior. In recent years, however, a new class of shadow banks has emerged—often operating in digital asset markets—that function largely outside existing regulatory frameworks and lack the protections that characterize traditional deposit-taking institutions (Kogan et al., 2024; Aiello et al., 2024a; Higgins, 2024).

In this paper, our aim is to shed light on depositor behavior during runs in this class of financial institutions. Our analysis focuses on Celsius, a crypto lending platform. Celsius accepted deposits in the form of cryptocurrencies such as Bitcoin (BTC) from both retail and institutional users, paid interest on those deposits, and lent the assets to borrowers. The company engaged in standard maturity transformation, a business model "identical to traditional banks" (Gorton and Zhang, 2024). Founded in 2017 by Alex Mashinsky, the platform expanded rapidly during the crypto boom, ultimately amassing more than $11 billion in digital assets from over 500,000 users worldwide. Celsius failed in mid-2022, when the collapse of the Terra (UST) stablecoin triggered a liquidity crisis that led the company to suspend withdrawals in June and file for Chapter 11 bankruptcy the following month.

As a largely unregulated entity, Celsius faced no supervisory oversight or disclosure requirements. In the absence of such protections, we consider whether depositor behavior is shaped not only by classical monitoring forces, such as institutional sophistication and financial exposure, but also by informal mechanisms rooted in culture, perceived information signals, and shared social beliefs. A rich literature shows that cultural norms shape how individuals interpret information, perceive risk, and respond to uncertainty (e.g., Guiso

et al., 2004, 2008; Stulz and Williamson, 2003). We hypothesize that these forces become especially important in shaping withdrawal decisions and post-collapse behavior when conventional depositor protections are weak or absent altogether.

Our analysis draws on transaction-level records from the Celsius bankruptcy proceedings. For users who withdrew funds, we apply crypto-forensic techniques to identify their on-chain wallets, allowing us to trace subsequent transactions following the platform's collapse. This linkage provides rare visibility into individual decision-making within a distressed shadow bank and how that shapes run-and-response dynamics. We use these data to examine whether, in the absence of formal monitoring, cultural traits substitute for or complement traditional information signals in shaping depositor behavior.

We begin our analysis with a descriptive overview of the depositor base. Celsius users were overwhelmingly retail, predominantly male, and ethnically diverse, with Anglo-Saxon, German, and Hispanic groups most common. Most accounts held only a few tokens, typically BTC, Ethereum (ETH), or stablecoins, and many users were passive, while a minority actively transferred or swapped assets. The distribution of holdings was highly skewed: the average balance exceeded $18,000, but the median was just $354.

Our pre-collapse analysis focuses on the intensive and extensive margins of stranded assets. We define *stranded assets* as the net value remaining in an account when Celsius halted withdrawals, calculated as initial holdings plus deposits minus withdrawals. These assets are stranded because they could not be liquidated after the bankruptcy filing. The intensive margin is captured by the *stranded asset ratio*, the share of stranded assets relative to total potential withdrawals (stranded assets plus withdrawals). The extensive margin is captured by the *stranded asset indicator*, which equals one if the stranded asset ratio exceeds 25%.

We first ask whether standard measures of monitoring incentives and ability are associated with stranded assets. In particular, we examine the relation between stranded balances and both institutional status and initial holdings on the platform. We find that both vari-

ables are negatively related to the likelihood and intensity of stranded assets. Institutional accounts were significantly less likely to be left with stranded balances, with stranded asset ratios 3.3–4.3 percentage points lower than comparable retail users. In probit specifications, institutional status reduced the probability of being stranded by about 8 percentage points. Similarly, larger initial holdings predicted lower stranded asset ratios, consistent with stronger incentives to monitor. These findings are broadly consistent with evidence from the banking literature (e.g., Iyer and Puri, 2012) as well as recent studies of Celsius (Gao and Sias, 2025) and other crypto platforms such as Terra–Luna (Liu et al., 2023a).

We also find that informational signals help explain withdrawal behavior, consistent with evidence from traditional financial institutions.[1] Withdrawals were negatively associated with Celsius-related news sentiment and with the returns and trading volume of CEL, a token linked to the platform. In contrast, withdrawals were positively associated with insider activity, driven primarily by transactions initiated by the CEO. These patterns suggest that depositors were highly responsive to both public information and insider behavior, with negative signals from either channel accelerating outflows.

Next, in our pre-collapse analyses, we examine how personal characteristics shape withdrawal behavior, with a particular focus on cultural heritage.[2] We focus on two dimensions: individualism (IDV) and power distance (PDI). Individualism captures the extent to which people value independent decision-making, while power distance reflects deference to authority and acceptance of hierarchy. We hypothesize that higher individualism shifts the marginal benefit of departing from the crowd, prompting depositors to act earlier and withdraw more aggressively when signals indicate weak fundamentals. In contrast, high power distance amplifies the weight placed on official reassurances and raises the marginal cost of

[1] See, for example, Gorton (1988), Iyer and Puri (2012), Iyer et al. (2016), Schmidt et al. (2016), and Cipriani et al. (2024).

[2] We draw on well-established measures of societal culture pioneered by Hofstede (1991). For a review, see Grennan and Li (2023). Recent work increasingly examines how culture shapes financial decisions (Grinblatt and Keloharju, 2001; Stulz and Williamson, 2003; Guiso et al., 2004, 2008; Chui et al., 2010; Li et al., 2013; Ahern et al., 2015; Eun et al., 2015; Nguyen et al., 2017; Pan et al., 2017, 2019; Fan et al., 2022; Wang et al., 2024).

deviating from them, fostering greater trust in authority and dampening run dynamics. To formalize these ideas, we extend a standard global games model of bank runs by embedding Hofstede's dimensions as preference shifters.

Our empirical findings align closely with these theoretical predictions. Higher individualism is associated with more timely and aggressive withdrawals, leading to lower stranded asset ratios. In contrast, higher power distance is linked to slower and weaker withdrawal responses, increasing the share of stranded assets. Additional evidence indicates that these cultural traits systematically shape how depositors interpret conventional information signals. More individualistic users react strongly to negative news and insider withdrawals, amplifying their impact and exiting more aggressively. By contrast, high power distance dampens the response to these same signals, consistent with greater deference to authority and reluctance to deviate from official recommendations from the Celsius CEO.

In the second part of our analysis, we study users' subsequent actions stemming from stranded assets on the Celsius platform. We link withdrawals from the bankruptcy filings to on-chain transactions to identify Ethereum wallets for a subset of users. Using a difference-in-differences framework, we compare portfolio adjustments of users with higher versus lower stranded balances over the 20 weeks surrounding the collapse. This design isolates how loss exposure shapes risk-taking behavior after the platform froze withdrawals. To interpret these post-collapse reallocations, we draw on three behavioral mechanisms, which include gambling-for-resurrection, flight-to-quality, and limited attention, that generate distinct predictions for how investors adjust risk exposures after realized losses.

We find that users with stranded assets adjust their portfolios in ways broadly consistent with gambling-for-resurrection after the collapse. On average, allocations to high-risk tokens increase, wallet concentration rises, and realized weekly returns tick up modestly for stranded users relative to others. At the same time, stranded users reduce their exposure to market-cap-dominant tokens such as Bitcoin and Ethereum and hold a smaller share of stablecoins, patterns that run counter to a flight-to-quality interpretation. Evidence for limited-attention

behavior is weaker but present: stranded users allocate slightly more to recent momentum winners and exhibit modestly more bursty trading. We further show that the severity of realized losses operates as an important channel, scaling the magnitude of these portfolio shifts and reinforcing the concentrated risk-taking predicted by reference-point dependent models of gambling-for-resurrection.

Finally, we show that post-collapse portfolio adjustments for those with stranded assets, in our matched-wallet subsample, exhibit significant heterogeneity based on cultural heritage. Users from more individualistic societies do not reallocate their portfolios as aggressively, resulting in decreased trading activity and fewer trades into low-risk tokens following the collapse. By contrast, users from more hierarchical cultures traded more. Taken together, these findings show that the cultural values and norms of society shape not only the timing of withdrawals but also the portfolio strategies that follow, influencing how investors respond to financial distress. We conclude with policy recommendations based on our findings that depositor cultural identity constitutes a double-edged sword. Namely, common identity is stabilizing in normal times, yet in stress, it synchronizes belief revisions and may amplify runs. While our evidence comes from a crypto shadow bank, the underlying mechanism is likely to extend to depositor identities more broadly (Akerlof and Kranton, 2000, 2005).

Finally, these conclusions are robust to an alternative fuzzy regression discontinuity design (FRDD) that exploits the mechanical timing freeze in withdrawals as a plausibly exogenous shock to loss exposure, allowing us to narrow our focus to those who tried but failed to execute trades in the window around the closure. In addition, because this setting provides a conservative test given that losses were sudden, severe, and mechanically determined, we view the modest heterogeneity we document as a lower bound, suggesting that the underlying behavioral mechanisms and underexplored identity-driven fragility channel may be even more salient in contexts with less abrupt constraints.

Overall, our paper contributes to several strands of literature. The closest work is Gao and Sias (2025), who also analyze the behavior of Celsius depositors. Our work differs in

several important ways. First, while Gao and Sias (2025) argue that depositor behavior was consistent with a bank run, we emphasize the role of information and how users process it in driving withdrawals, consistent with a fundamentals-based story that does not require strategic complementarities. Second, our results show that cultural characteristics can both dampen and heighten depositor responses to information flows, shaping the timing and intensity of withdrawals. Third, we employ crypto-forensic methods to link Celsius bankruptcy filings to user wallets, allowing us to study post-collapse behavior.

More generally, our study contributes to the growing tokenomics and DeFi literature (Yermack, 2017; Cong and He, 2019; Cong et al., 2021; Makarov and Schoar, 2022; John et al., 2023). The economics underlying these projects vary from staking rewards (Cong et al., 2022; Augustin et al., 2023), to borrowing and lending assets (Bertomeu et al., 2023; Lehar and Parlour, 2023), to facilitating decentralized exchange (Lehar and Parlour, 2024; Harvey et al., 2024), to delegating business and investment decisions to a decentralized community (Han et al., 2023; Appel and Grennan, 2023, 2024; Cong et al., 2025), to stablecoins (Catalini et al., 2022; Whited et al., 2023; Niepelt, 2024) and beyond. The closest vein of this research analyzes digital asset user demographics (Auer et al., 2023; Aiello et al., 2024a,b; Kogan et al., 2024). We complement this work by showing that digital asset users rely on formal and informal monitoring mechanisms, such as culture, which makes them susceptible to cheap talk. Thus, our study helps bridge DeFi with TradFi and the much broader literature examining depositor behavior and bank fragility (Chen et al., 2024), including evidence that depositor networks shape monitoring and run dynamics (Goldstein and Pauzner, 2005; Iyer and Puri, 2012; Iyer et al., 2016; Choi et al., 2024).

Second, our work extends an extensive behavioral and social finance literature (e.g., see reviews by Baker et al. (2007) and Gorton et al. (2022)) to the digital asset context, where a nascent literature is emerging (D'Acunto et al., 2019, 2023, 2024). Specifically, in his presidential address, Hirshleifer (2020) argues we must understand how social norms and interactions between people lead to transmission biases and their potential for influencing

financial decisions. By examining societal culture as a coarse signal in the decentralized context, we establish that even in technically trustless settings, users rely on these deeply ingrained cultural traits to make decisions. This is consistent with research showing informal institutions like societal culture (Stulz and Williamson, 2003; Guiso et al., 2006), social capital (Guiso et al., 2004; Servaes and Tamayo, 2017), and specific cultural values and norms (Guiso et al., 2015; Graham et al., 2022; Mishra et al., 2022) have a pronounced influence on financial decision-making even in banking contexts (Fisman et al., 2017; Demiroglu et al., 2021).

Third, we contribute to research on policy responses to digital downturns such as those experienced by Terra-Luna and others (Ilabaca and Nguyen, 2023; Patel and Rose, 2023; Liu et al., 2023b; Ma et al., 2025). Our crypto-forensic techniques provide very granular data that enables us to test new theories and contribute to studies analyzing cybercrime (Foley et al., 2019; Lyandres and Rabetti, 2023; Cong et al., 2023, 2024b; Kotidis and Schreft, 2025). Finally, our findings have meaningful regulatory implications (Guseva, 2021, 2022; Grennan, 2025; Cong et al., 2024a; Harvey et al., 2024).

2. Institutional Background

2.1. Business Model and Operations

Celsius Network, founded in 2017 under the leadership of Alex Mashinsky, positioned itself as a trustworthy alternative to traditional banks.[3] The company's website emphasized "fair interest, low rates for loans, and lightning quick transactions," while claiming robust compliance programs supported by veteran anti-money laundering (AML) professionals. In practice, Celsius operated much like a crypto retail bank. It offered high-interest savings

[3]Celsius maintained a dual corporate structure to facilitate its global operations. In the United States, it operated as Celsius Network LLC, incorporated in Delaware in June 2021 and headquartered in Hoboken, New Jersey. In the United Kingdom, it operated as Celsius Network Limited, incorporated in England and Wales in February 2018 and headquartered in London.

accounts, collateralized loans, and rewards paid in its native token, CEL. Users' deposits were structured as unsecured loans to Celsius, which generated revenue by lending those assets to institutional borrowers and sharing the proceeds with depositors. Marketing emphasized transparency, accessibility, and community focus, distinguishing Celsius from both banks and other cryptocurrency platforms. The company managed a wide range of digital assets, with particular exposure to BTC and Ethereum balances.

A central feature of Celsius's business model was the CEL token. Mashinsky frequently asserted that CEL's price reflected the company's underlying value. The token was marketed as the backbone of a self-reinforcing growth model in which Celsius's success, customer rewards, and token appreciation were mutually reinforcing. As depicted in Figure 1, the company described a "flywheel" where new deposits attracted through marketing would generate profits; those profits would fund CEL purchases to pay rewards; rising CEL prices would then attract additional users, perpetuating the cycle. This narrative was core to Celsius's pitch to depositors and investors alike.

Despite these promises, Celsius quickly departed from its stated model. Its 2018 initial coin offering fell short of expectations: while the firm projected raising $50 million through the sale of 325 million CEL tokens, it sold only 203 million tokens for $32 million. Celsius concealed this shortfall, and Mashinsky reneged on his commitment to purchase the remaining unsold tokens, leaving a significant gap in the company's capitalization. This episode foreshadowed a broader pattern of opacity and misrepresentation.

Beginning in 2020, Celsius engaged in aggressive efforts to manipulate the price of CEL. The firm abandoned its original practice of buying tokens only to meet reward obligations and instead adopted what insiders termed the "OTC Flywheel." This strategy included timing purchases to prop up CEL's price, placing "resting" orders to counter declines, and offsetting private over-the-counter sales with public market purchases to maintain upward pressure. The scheme was highly effective: between March 2020 and June 2021, CEL's price increased by 14,751%, far outpacing the broader cryptocurrency market.

The inflated token price served several purposes. First, it dramatically boosted Celsius's reported balance sheet, with CEL holdings valued at $1.5 billion by December 2021 (up from $6.6 million in February 2019), despite internal recognition that CEL was effectively "worthless." Second, it enabled substantial insider enrichment. Mashinsky personally sold at least 25 million CEL tokens for approximately $68.7 million, while co-founder S. Daniel Leon realized at least $9.7 million. To offset downward price pressure from these sales, Celsius often increased its own market-making activities, leading one employee to remark that the firm was "using users' USDC to pay for employees' worthless CEL."

The consequences of this strategy were severe. Because Celsius could not generate sufficient yield from its crypto lending to fund ongoing CEL buybacks, it began diverting customer assets, including Bitcoin and Ethereum, for these purchases. By early 2021, the company had created a shortfall of roughly $300 million in stablecoins to cover these activities. In total, Celsius spent at least $558 million buying CEL, ultimately acquiring 223 million tokens, which is more than it had ever sold publicly, and holding roughly 95% of all CEL in existence by the time of its bankruptcy. Customer funds were thus redirected to sustain the token's price rather than to generate legitimate returns.

The firm's manipulation extended beyond token markets to its core promise of paying depositors competitive yields. Although Celsius publicly claimed to distribute "up to 80% of its revenues" to customers, reward rates were not based on actual investment performance. Instead, they were set to attract users and outcompete rivals, often exceeding the revenues the company could generate. When questioned by regulators, Celsius admitted there was no correlation between customer rates and investment yields. Until July 2021, the company had no formal reward policy, and even afterward, rates remained untethered to operating performance. In effect, customer payouts were subsidized by new deposits and asset sales rather than sustainable investment returns, leaving Celsius with a structurally unsound and ultimately insolvent business model.

2.2. Account and Transaction Types

Customer funds were held in three types of accounts: Earn, Custody, and Withhold. Customers could engage in a wide range of transactions, including deposits, transfers, swaps, loan-related payments, and withdrawals. Online Appendix A provides definitions of the types of accounts and transactions available to Celsius users.

Initially, all customer deposits were pooled in a main wallet. Following regulatory changes in April 2022, Celsius was required to separate customer assets into Custody, Earn, or Withhold accounts. By design, new deposits flowed first into Custody. To earn yield, customers had to transfer assets into Earn, while Custody remained the default for transfers, swaps, and collateralization. Withhold accounts were introduced for customers in jurisdictions where Celsius lacked appropriate licenses, preventing new deposits into Earn.

Although Celsius's FAQs described strict distinctions across account types, bankruptcy data reveal blurred boundaries. Transactions such as loan interest payments, collateral postings, and even withdrawals appear in Withhold accounts. Earn accounts—which were supposed to be limited to interest accruals and transfers—also display swaps and withdrawals. These inconsistencies point to systematic commingling of customer assets, undermining Celsius's claim that Custody accounts were segregated and owned by users.

2.3. Timeline of Celsius Collapse

Between April and July 2022, Custody wallets experienced repeated shortfalls, often covered by transfers from the firm's main accounts. Liquidity problems intensified in May 2022 following broader market turmoil, including the collapse of Terra's UST and LUNA tokens. Between May 9 and May 24, customer withdrawals exceeded $1.4 billion, nearly depleting the company's capital. On June 12, Celsius froze all withdrawals, swaps, and transfers, citing "extreme market conditions." Despite these restrictions, internal deficits in Custody wallets persisted, with Celsius transferring nearly $48 million in late June to mitigate gaps. By the time of its bankruptcy filing on July 13, 2022, Custody wallets again

faced substantial shortfalls, later estimated at 3.2 million coins (approximately $16.9 million) as of October 2022.

Celsius's collapse underscored the fragility of crypto lending platforms and the risks associated with opaque business practices. At the time, it was the third major crypto firm to declare bankruptcy in 2022. Key dates are summarized below:

2017: Celsius Network founded.

March 2018: Platform launch and $50 million ICO of CEL token.

June 2018: Release of Celsius mobile application.

Sept. 29, 2020: Terms of Use revised to transfer ownership of customer assets in Earn accounts to Celsius.

April 12–15, 2022: Celsius announces and launches Custody program for non-accredited U.S. investors.

May 7–12, 2022: Collapse of Terra (UST) and LUNA roils crypto markets.

June 12, 2022: Celsius freezes withdrawals, swaps, and transfers.

June 30, 2022: Celsius hires restructuring advisers.

July 13, 2022: Celsius files for bankruptcy, citing contagion from Terra's collapse.

3. Theoretical Framework

3.1. Pre-collapse Behavior

Because Celsius was a shadow bank, standard theories of moral hazard in banking do not explain depositor behavior. Instead, our motivation draws from theory on market discipline and monitoring behavior. In traditional settings, monitoring occurs through well-defined contractual and institutional arrangements such as fiduciary duties, collateral, or creditor rights (Shleifer and Vishny, 1997). In the case of Celsius, however, these contractual protections were weak or absent, potentially elevating the importance of informal monitoring mechanisms.

We distinguish between two types of monitoring mechanisms: formal, established by law and institutions, and informal, shaped by cultural heritage and social norms. This distinction follows North (1991), who emphasizes that institutions consist of both formal rules and informal constraints. To capture depositor behavior in our setting, we extend the global-games framework of Morris and Shin (1998) to incorporate cultural heterogeneity. Depositors choose whether, and how much, to withdraw from a distressed platform. Their decisions depend not only on fundamentals and noisy signals, as in the canonical model, but also on cultural dimensions that potentially influence monitoring and withdrawal behavior.

To capture cultural differences that potentially affect monitoring, we rely on Hofstede's measures of societal culture (Hofstede, 1991), Hofstede scores societies along six dimensions; we focus on two measures: individualism (IDV) and power distance (PDI) because they generate clear, opposing predictions. Individualism reflects the extent to which people value independent decision-making over group conformity, while power distance captures how much people defer to authority and accept hierarchical order. These traits matter because they shape how depositors interpret information signals and whether they respond by following peers and leadership or by acting independently.

The intuition for the cultural framework is straightforward. Individualism lowers the cost of deviating from the crowd, leading depositors to act earlier and withdraw more aggressively when their information suggests weak fundamentals. Power distance, by contrast, increases deference to authority, both by overweighting official reassurances and by imposing a penalty for disobeying leaders' instructions. As a result, high-PDI depositors delay action and, conditional on withdrawing, do so less aggressively. Figure 2 illustrates this mechanism: individualism shifts the marginal benefit curve upward, while power distance shifts the marginal cost curve upward, producing opposite comparative statics for stranded assets.

From this framework, two testable propositions follow:

> *Proposition 1: Extensive margin.* Suppose the authority figure, such as CEO Mashinsky, recommends holding. Holding fundamentals and balances fixed, higher individu-

alism raises the initiation cutoff, reducing the probability of being stranded. Higher power distance lowers the cutoff, increasing the probability of being stranded.

Proposition 2: Intensive margin. Conditional on initiating withdrawals, higher individualism increases the withdrawal share, lowering the stranded asset ratio. Higher power distance reduces the withdrawal share, raising the stranded asset ratio.

Online Appendix section B develops this model formally and proves the uniqueness of cutoff strategies. In our model, we emphasize how cultural traits interact with fundamentals to shape depositor behavior. This contrasts with prior research, which has shown that culture can mitigate or amplify fragility. In traditional banking, cultural proximity and strong relationships often reduce adverse outcomes (Iyer and Puri, 2012; Koudijs et al., 2021; Fisman et al., 2017), whereas in crypto, pseudonymity weakens these channels. Cultural networks can also provide early warnings (Hirshleifer and Teoh, 2003; Cohen et al., 2008), but they may foster echo chambers and groupthink that delay recognition of problems (Hirshleifer, 2001; Cookson et al., 2022). Our framework clarifies this ambiguity by embedding cultural heritage into a global-games setting, showing how withdrawal thresholds and intensity depend not only on fundamentals but also on how cultural norms shape the interpretation of signals.

3.2. Post-collapse Behavior

Once Celsius froze withdrawals, the strategic environment changed sharply. The coordination problem that governs the strategic behavior of depositors pre-collapse disappears, and instead, they face a portfolio-allocation problem for the assets they retained. In this stage, we draw on ideas previously described in the behavioral finance literature such as portfolio choice after realized losses, trust shocks, and limited attention.

We consider three mechanisms that offer competing predictions for post-collapse reallocation. The first is loss-induced risk-taking, or gambling-for-resurrection. A long literature shows that realized losses shift investors into the loss domain of their reference-dependent

utility function, raising the appeal of high-volatility or skewed assets (Thaler and Johnson, 1990; Barberis et al., 2001). Empirically, Imas (2016) demonstrates that loss realization increases subsequent risk taking among individual investors. Relatedly, Heimer et al. (2025) show that investors exhibit dynamic inconsistency in risky choice. Although inventors plan to cut losses and exit, they systematically do the opposite, holding losers and continuing risk after losses while cutting gains early, in both brokerage data and laboratory settings. These outcome-dependent reversals are consistent with cumulative prospect theory and imply that Celsius users facing salient losses may have re-risked, concentrated positions, or added new funds in attempts to recover prior wealth.

A second mechanism predicts the opposite response. When intermediary trust erodes, investors commonly shift toward safer assets in a flight-to-quality mechanism. In macro-finance models, trust shocks generate precautionary demand for safe assets (Caballero and Krishnamurthy, 2008). Household-finance studies similarly show that personal financial losses produce persistent reductions in risk taking and greater demand for safety (Malmendier and Nagel, 2011; Gurun et al., 2017). Applied to Celsius, this mechanism predicts reallocations toward fiat-backed stablecoins and other dominant tokens, reductions in trading intensity, and more diversified post-collapse portfolios.

A third mechanism arises from limited attention in the aftermath of the collapse. Under cognitive load or information overload, retail investors rely disproportionately on salient cues rather than full screening. Barber and Odean (2007) show that individual investors allocate toward high-visibility or attention-grabbing assets when attention is scarce, building on earlier evidence of salience-driven trading (Barber and Odean, 2000, 2001) and extensive survey evidence (Barber and Odean, 2013). Given the emotionally charged and noisy informational environment surrounding the Celsius collapse, this mechanisms predicts shifts toward salient tokens, such as momentum leaders or highly-visible tokens, as well as episodic trading bursts. This channel aligns with the news-utility framework, in which investors optimally limit monitoring and adopt heuristic rules to avoid the psychological costs of bad news (Pagel, 2018)

and empirical evidence (Olafsson and Pagel, 2025).

Although distinct, these mechanisms may manifest differently across the heterogeneous depositor base. This means that the same cultural traits that shaped pre-collapse withdrawal incentives may continue to matter in the post-collapse period. To discipline thinking about culture in the post-collapse period, we focus on two channels. First, individualism governs the action cost of portfolio adjustment. Higher-individualism depositors attach lower psychological cost to deviating from peer norms, and thereby, are willing to go against the norm. These actions imply those from individualistic culture are likely to independently update in response to their experienced shocks.

Second, power distance governs the narrative-weighting channel. This means that higher-power distance depositors place greater weight on statements from perceived authorities or dominant narratives in information-sparse environments, amplifying inertia when guidance favors caution but increasing flow sensitivity when salient signals become focal. Together, these channels generate testable predictions. Individualism should scale the magnitude and timing of post-collapse rebalancing, while power distance should increase persistence of pre-collapse allocations and raise exposure to attention-driven reallocations.

4. Data and Empirical Design

4.1. User Data

We construct our dataset by linking four primary sources at the individual depositor level: (i) transaction-level bankruptcy disclosures, (ii) extended blockchain activity, (iii) token price and risk data, and (iv) depositor demographics and cultural characteristics. This linkage allows us to study heterogeneous depositor behavior and portfolio outcomes surrounding the Celsius collapse.

Our first source is comprehensive transaction-level data from Celsius's Chapter 11 filings, covering April 14 through June 12, 2022, the 90 days preceding the withdrawal freeze. Each

observation records creditor ID, date, account type (Earn, Custody, Withhold), direction, coin type, quantity, USD value, and transaction classification. We exploit the "Interest and Rewards" category to map pseudonymous wallet addresses to depositor identities.

Second, we extend these records using blockchain transaction histories for 2022, obtained via the Moralis API. Unlike Ethereum-only sources such as Etherscan, Moralis provides multi-chain coverage, enabling us to observe depositor activity both before and after the collapse, as well as holdings across non-Celsius platforms. While bankruptcy filings capture Celsius-specific balances at July 13, 2022, the extended data reflect multi-platform engagement and portfolio diversification.

Third, we merge digital asset holdings with token price and risk data to examine depositor responses in terms of risk and return. Finally, we incorporate demographic and cultural characteristics inferred from depositor names, as described below. This linked dataset enables us to trace heterogeneous depositor behavior and portfolio implications across economic, cultural, and regulatory dimensions.

4.1.1. Demographic and Cultural Characteristics

We obtain non-redacted bankruptcy filings that disclose the names of all account holders with activity in the 90-day pre-petition period. We use these names to infer gender, ethnicity, and cultural attributes. Gender is identified through a three-stage algorithm combining UCI's "Gender by Name" dataset with the Global Gender Predictor and Gender Guesser packages.[4] This procedure yields high-confidence matches for 87% of names. Ethnicity is inferred using three classifiers: (i) Ethnicity dictionaries, (ii) EthnicClassifier from the `ethnicseer` package, and (iii) RaceBERT, a transformer-based model trained on U.S. census data.[5] Results are integrated to assign standardized ethnicity categories (e.g., "Arabic/Middle Eastern"). This process yields high-confidence ethnicity assignments for 91%

[4]UCI Gender by Name: https://doi.org/10.24432/C55G7X. Global Gender Predictor: https://github.com/attract-ai/global-gender-predictor. Gender Guesser: https://pypi.org/project/gender-guesser/.

[5]Ethnicseer: https://github.com/pucktada/ethnicseer. RaceBERT: https://pypi.org/project/racebert/.

of the sample. Finally, we map depositor ethnicity classifications to Hofstede's cultural dimensions (Hofstede, 1991), which capture cross-country variation along six dimensions: power distance, individualism, masculinity, uncertainty avoidance, long-term orientation, and indulgence. These dimensions provide a framework to interpret behavioral differences in depositor responses to the Celsius collapse.

4.1.2. Blockchain Transactions and Wallets

We use the Moralis API, a blockchain data indexing service, to collect on-chain transaction and wallet-holding data related to identified wallets from the Celsius Network bankruptcy filings. The data collection process encompasses pulling snapshots of the wallet holdings at a specific block height corresponding to a calendar day. This allows us to observe daily holdings data for the quarter before the downfall of the Celsius Network and to understand what particular wallets with stranded assets did in response.

We classify digital assets held by wallets using both external ratings and manual verification. Moralis provides a token risk score ranging from 1 (highest risk) to 99 (lowest risk). Established assets such as Ethereum receive the maximum rating of 99. To complement this measure, we manually review token addresses and names, allowing us to classify assets into three risk tiers:

- **Low risk**: Layer-1 protocols and all stablecoins (fiat-backed, crypto-backed, or hybrid).
- **Medium risk**: All remaining tokens not categorized as high or low risk.
- **High risk**: Tokens associated with memecoins, gaming, gambling, gamified elements, or derivatives and other instruments enabling outsized speculation via leverage.

In addition to the type of holdings, we also calculate risk-adjusted wallet returns using the crypto-factor model (Liu et al., 2022). The risk factors are analogous to those in the

traditional factor model for equities, but applied to digital assets. The crypto factors include a cryptocurrency market factor, a size factor, and a momentum factor.

4.2. Stranded Assets

Many of our tests examine the intensive and extensive margins of stranded assets. We define *Stranded Assets* as the amount of initial holdings plus deposits minus withdrawals in US dollars. *Initial holdings* represents the starting value of assets in the account. It is the baseline amount from which any changes in asset value due to transactions is measured. Adding *Deposits* to the initial holdings accounts for any additional funds or assets placed into the account after initial holdings are established. Subtracting *Withdrawals* from the sum of initial holdings and deposits reflects the reduction in asset value due to funds being taken out of the account. Thus, *Stranded Assets* captures the net value of assets that remain in the account after all transactions occur. These remaining assets are considered stranded because they are still in the account at the time of the bankruptcy and cannot be easily converted to cash or otherwise utilized. The *Stranded Asset Ratio* is the amount of stranded assets in USD divided by stranded assets plus withdrawals. The *Stranded Asset Indicator* equals 1 if the user has a *Stranded Asset Ratio* $\geq 25\%$.

4.3. Empirical Design

Our empirical strategy is multi-pronged. First, we examine the cross-sectional relation between monitoring incentives and the likelihood that depositors held stranded assets on Celsius at the time of bankruptcy. For this descriptive analysis, our primary specification estimates withdrawal intensity using OLS, with the dependent variable defined as the *Stranded Asset Ratio*. We complement this with a logistic regression that models the binary decision to withdraw assets, captured by a stranded asset indicator.

The second part of our empirical strategy examines differences in behavior between individuals with and without stranded assets. We estimate the following difference-in-differences

(DiD) specification on a balanced panel of weekly wallet-level observations, including wallet and week fixed effects:

$$Y_{it} = \alpha + \beta_1 \left(\text{Treat} \times \text{Post}\right)_{it} + \beta_2 \left(\text{Treat} \times \text{Post} \times \text{TL}\right)_{it} + \beta_3 \left(\text{Post} \times \text{TL}\right)_{it} + \gamma_i + \rho_t + \varepsilon_{it}, \quad (1)$$

where Y_{it} is an outcome such as the number of transactions for wallet i in week t. $Treat$ indicates a wallet with stranded assets on Celsius, and $Post$ is an indicator for dates on or after June 12, 2022, when withdrawals were suspended. TL identifies wallets exposed to the Terra-Luna crash, which we define as those users whose wallets either held or traded Terra or Luna in the 2022 calendar year. Wallet fixed effects (γ_i) absorb time-invariant wallet characteristics, while weekly fixed effects (ρ_t) absorb common time shocks. We include $(Treat \times Post \times TL)_{it}$ to allow treatment effects to vary by exposure to Terra-Luna wallets, and we include $(Post \times TL)$ to capture the potential for Terra-Luna-exposed users to transact more or less in the post period. The coefficient of interest is β_1, which measures the average effect of stranded assets. Standard errors are clustered at the wallet level to account for within-wallet correlation.

We extend this framework to a difference-in-differences-in-differences (DDD) design to test whether treatment effects differ systematically by cultural traits. The first difference is between wallets with and without stranded assets, the second between pre- and post-collapse periods, and the third across cultural dimensions:

$$\begin{aligned} Y_{it} = \beta_1(\text{Treat} \times \text{Post})_{it} + \beta_2(\text{Treat} \times \text{Post} \times \text{TL})_{it} \\ + \beta_3 \left(\text{Post} \times \text{TL}\right)_{it} + \beta_4(\text{Culture} \times \text{Treat} \times \text{Post})_{it} + \beta_5(\text{Culture} \times \text{Post})_{it} + \gamma_i + \rho_t + \varepsilon_{it}. \end{aligned} \quad (2)$$

Here, β_4 captures an additional culture-based change to the relation between being caught with stranded assets and subsequent trading activity. Including $(Culture \times Post)_{it}$ allows β_5 to capture the more general culture-based response to the collapse of Celsius, something we also explore. As before, we include wallet and weekly fixed effects, allow treatment to

vary by Terra-Luna exposure, and cluster the standard errors at the wallet level.

As with any DiD design, a causal interpretation hinges on the parallel trends assumption (Olden and Møen, 2022). One important threat to such an interpretation is the collapse of the Terra-Luna stablecoin. From May 7 to May 12, 2022, the algorithmic stablecoin TerraUSD (UST) depegged from its $1 target and collapsed to 35 cents while its stabilizing companion token LUNA simultaneously crashed from $80 to near-zero, resulting in the failure of Terra-Luna. Around the same time, withdrawals from Celsius Earn accounts peaked (Figure 3). This spike is followed by significant fluctuations in both withdrawals and deposits, with the outgoing values consistently higher than the incoming values throughout the period. To account for this confounding event, the above specifications specifically control for whether wallets had exposure to Terra-Luna prior to its crash. In addition, just as with our regression specifications, we remove the influence of the Terra-Luna event from our pre-trend analysis.

[Insert Figure 3 here]

Next, we assess whether the evidence is consistent with the assumption of parallel trends holding. Specifically, we compare the pre-collapse trends in the weekly wallet transactions for both low-risk tokens and high-risk tokens between those with and without stranded assets. While it is not possible to definitively establish if the assumption is met, these tests can provide suggestive evidence in support (Rambachan and Roth, 2023). Figure 5 depicts the extent to which the treatment and control groups were on parallel trajectories after removing the confounding Terra-Luna event.

[Insert Figure 5 here]

In this figure, the point estimates reflect the relative differences in high and low-risk transactions between those with and without stranded assets across weeks. Blue dots and lines show the point estimates and confidence intervals across weeks. Based on these parallel trend tests, the figure shows similar high- and low-risk transaction patterns between

those with and without stranded assets preceding the Celsius collapse. We formally test whether the pre-withdrawal halting coefficients differ from zero using the approach proposed by Freyaldenhoven et al. (2021). The statistical tests fail to reject the null hypothesis that these coefficients equal zero, with p-value of 0.20 and 0.40 for the two types of transactions, which suggests comparable transaction volumes.

5. Summary Statistics

5.1. Depositor Demographics

Table 1 reports summary statistics on depositor demographics. The dataset includes 492,000 depositors, of which 99.6% are individuals and only 0.4% are institutions, underscoring that Celsius's user base was overwhelmingly retail. Among individuals, 74.4% are male, 19.8% female, and 5.9% unclassified.

The depositor base is ethnically diverse. Anglo-Saxon depositors represent the largest group (26.5%), followed by German (12.7%), Hispanic (9.3%), French (9.5%), Italian (9.2%), and Chinese (6.95%). Ethnicity could not be identified for 8.8% of depositors. Cultural heritage measures, based on Hofstede's framework, yield an average power distance score of 55.7 (on a 0–100 scale), suggesting that the typical depositor comes from societies moderately accepting of hierarchical authority. In addition, individualism ranked high (59.3) as did uncertainty avoidance (62.2).

[Insert Table 1 here]

To contextualize Celsius depositors, we benchmark against survey data and prior studies. The Federal Reserve Bank of Atlanta's Survey and Diary of Consumer Payment Choice shows that 10% of U.S. households owned crypto in 2021—2022, with investment cited as the main motive.[6] Gender and ethnicity patterns are broadly comparable to Celsius, though Celsius

[6]More recent survey evidence shows it is 24%, but we wanted to benchmark to data from the same time period.

skewed more male (74.4% vs. 67.5%) and had fewer Black and multiracial depositors, while Hispanics were more represented in our sample. The Atlanta Fed survey also shows that crypto owners are disproportionately younger and higher income.

We also compare our statistics with those of three academic studies. Kogan et al. (2024) analyze global eToro traders and find ethnic distributions similar to Celsius (e.g., German 13.2% vs. 12.8%). Aiello et al. (2024b) use U.S. banking data and report higher adoption (17.5%) but a user base that is whiter, less Asian, and less male than Celsius. They also report lower mean holdings ($8,147 vs. $18,606). Weber et al. (2023), using Nielsen Homescan, find 12% of households own crypto, with owners disproportionately male, younger, and less likely to be white, again consistent with our findings.

Overall, Celsius depositors resemble the broader crypto investor population but represent a niche segment relative to traditional bank customers. A closer analogy may be specialty banks such as Silicon Valley Bank or Abacus Federal Savings Bank, which built advantages by catering to concentrated depositor bases that, like our setting, later became sources of fragility under stress.

5.2. Properties of Earn Accounts

Table 2 summarizes users' account holdings on Celsius. Panel A shows that nearly all users utilized Earn accounts, while 11% used Custody accounts and about 1% had Withhold accounts. On average, Earn accounts held 3.3 tokens (median of 2). Bitcoin was the most common holding (71%), followed by Ethereum (42%) and stablecoins (27%). About 75% of accounts also held other tokens outside these categories.

[Insert Table 2 here]

Panel C of Table 2 summarizes Earn account transactions. On average, each account had 1 incoming and 1 outgoing transaction. Incoming transfers averaged $1,761 in Bitcoin, $1,368 in Ethereum, and $1,372 in stablecoins. Outgoing transfers were larger, averaging

$3,888 in Bitcoin, $3,004 in Ethereum, and $2,554 in stablecoins. Interest earnings were small relative to transfers: the average account earned only $172 over the sample period, including $36 from Bitcoin, $42 from Ethereum, $35 from stablecoins, and $60 from other tokens.

Panel D reports Earn account balances. Average initial holdings were $18,606, with a median of just $354, highlighting the extreme skew in asset distribution across depositors. A few very large accounts held the majority of assets, while most accounts were very small. The mean stranded asset ratio was 0.83, indicating that the vast majority of user assets were trapped on the platform at bankruptcy.

Figure 6 graphs the distribution of initial holdings in the Earn Accounts for the sample. There is a predominance of low initial holdings for Celsius users. The chart shows that a large majority of accounts have initial holdings of less than $10,000, as indicated by the tallest bar, which represents approximately 70% of the total accounts. As the figure shows, the category for accounts with initial holdings of $50,000 or more is also noticeable. Thus, there is also a sizable fraction of accounts with large holdings, although it is noticeably smaller than the lowest range.

[Insert Figure 6 here]

6. Results

6.1. Monitoring

We begin our analysis by examining the relation between monitoring incentives and the degree of stranded assets on Celsius. Specifically, we focus on two depositor characteristics: whether the user is an institutional investor (as opposed to retail) and the size of their initial balance on the platform. Both dimensions have been linked to monitoring ability and incentives in prior research. Institutional investors are often better equipped to collect and process information, and thus play a central role in monitoring across capital markets.

Similarly, investors with larger stakes face greater exposure and stronger incentives to monitor, consistent with classic models of blockholder governance. Applying these insights to the Celsius setting, we test whether institutions and large-balance users were more likely to withdraw in anticipation of the platform's collapse, thereby avoiding stranded assets.

Table 3 reports our findings. The dependent variable is the stranded asset ratio and an indicator for stranded assets in Columns 1–2 and 3–4, respectively. Across specifications, the coefficient on the institution indicator is negative and statistically significant, indicating that institutional depositors were less likely to be left with stranded assets. Economically, the effect is meaningful. Institutions exhibit stranded asset ratios that are 1.5–4.7 percentage points lower than otherwise similar retail users. Likewise, in the probit specifications (Columns 3 and 4), institutional status reduces the probability of being left with stranded assets by roughly 8 percentage points. Initial account size also predicts withdrawal behavior. Larger depositors were systematically less likely to have assets trapped on the platform, consistent with the notion that monitoring incentives increase with exposure. Together, these results suggest that both institutional sophistication and financial exposure played a central role in shaping depositor responses during the Celsius collapse. These findings are similar to those reported by Gao and Sias (2025).

[Insert Table 3 here]

6.2. Informational Signals

We next assess the role of information in driving withdrawals from Celsius. To get a sense of the variation in the potential information signals, Figure 4 plots daily withdrawals from Celsius Earn accounts by the CEO and other insiders prior to Celsius halting withdrawals. The grey shaded region highlights the period of the Terra–Luna collapse. Insider withdrawals (gold line) are highly concentrated in that period. CEO withdrawals (maroon line) are notable for two reasons. First, their magnitude is roughly equivalent to all other insider withdrawals. Second, while the CEO's withdrawals are clustered with other insider

withdrawals, there is little correlation with user withdrawals (navy line) outside the Terra-Luna window. This suggests that insiders were likely acting on superior information or heightened awareness of platform fragility.

[Insert Figure 4 here]

The traditional signals that we examine extend beyond insider trades to include news sentiment about Celsius, and the returns and trading volume of the CEL token. Table 4 reports our findings. Across all specifications, negative sentiment in Celsius-related news is strongly associated with withdrawals. The coefficients on the news sentiment variable are negative and highly significant, implying that unfavorable media coverage increased both the likelihood and the magnitude of user withdrawals. This finding highlights the sensitivity of retail investors to information frictions and reputational shocks, consistent with evidence from traditional banking contexts where depositor behavior is shaped by public signals.

[Insert Table 4 here]

Declines in CEL token performance also predicted withdrawals. Both CEL returns and trading volume enter with negative coefficients, suggesting that deteriorating token prices and heightened trading activity were interpreted as warning signs of distress. Increased trading volume could indicate intense selling pressure, especially when accompanied by falling prices. Finally, insider withdrawals are positively and significantly associated with user withdrawals. The estimates indicate that when insiders removed assets, other users were more likely to follow suit, both in terms of participation and withdrawal intensity. Thus, these findings are consistent with Celsius depositors acting in a highly responsive manner to both traditional informational signals and crypto-specific market signals.

6.3. Cultural Determinants of Withdrawals

We next investigate whether depositor cultural heritage influenced the likelihood of withdrawing assets from Celsius. Table 5 reports regressions of the stranded asset ratio (Columns

1–3) and a stranded asset indicator (Columns 4–6) on Hofstede's cultural dimensions, focusing on power distance (PDI) and individualism (IDV). These dimensions capture differences in societal attitudes toward hierarchy and autonomy, which may shape financial decision-making under stress.

The results indicate that depositors from higher power distance cultures were more likely to leave assets stranded on the platform. The coefficients on PDI are positive and statistically significant in most specifications. Similarly, the probit model in Column 6 suggests that higher power distance is associated with a significantly greater probability of being stranded. These findings are consistent with the notion that individuals in hierarchical societies may place greater trust in centralized authority and be less inclined to monitor financial institutions closely.

Next, we investigate the propositions from our theoretical framework that elements of societal culture can systematically alter how Celsius users interpret traditional information signals. For example, when the authoritative CEO of Celsius repeatedly told customers to continue holding their assets with Celsius during interviews, our framework predicts that those users from higher power distance societies would defer to this messaging even when they could observe the traditional information signal that he and other insiders were making large withdrawals. Thus, the culturally differentiated reaction is a lower amount of withdrawals for those from high power distance societies. In contrast, those from individualistic societies would do the opposite and weight the insider withdrawals more heavily and therefore withdraw more than those from less individualistic societies.

Consistent with this notion, the evidence in Table 6 suggests that cultural background does not dominate fundamentals, but instead conditions how the Celsius user perceives the traditional information and how it should be translated into action. The same informational shock can generate sharply different withdrawal responses depending on the user's cultural priors. In more individualistic societies, positive news sentiment is interpreted as validation of one's judgment, reducing the incentive to withdraw. At the same time, insider withdrawals

are taken as cues to act quickly and independently, amplifying run dynamics. We find that users from more individualistic societal cultures are even less likely to withdraw when sentiment is positive. Yet, they are more likely to mimic insider withdrawals. The economic magnitude of the interaction terms suggests that they typically shift withdrawal probabilities by 3–5 percent relative to the baseline, thereby pointing to systematic amplification through cultural priors for users from individualistic societies.

[Insert Table 6 here]

Other elements of societal culture operate in the opposite direction. For example, users from high-power-distance societies appear less willing to copy insider behavior. A plausible interpretation is that insider privileges are viewed as legitimate prerogatives of authority, not as signals that ordinary depositors should copy. Thus, even credible signals, like insider withdrawals, are discounted or even ignored in these cultural contexts. Specifically, the evidence in Column 2 suggests that depositors from societies with higher power distance are less responsive to both sentiment and insider withdrawals. The mediating influence of these cultural elements supports long-standing sociological theories of authority and deference. In high-power-distance societies, insiders' privileges may be interpreted as legitimate exceptions rather than as warnings relevant to ordinary depositors. In the Appendix, we confirm that these cultural results yield similar inferences when we examine a withdrawal indicator rather than the withdrawal amount. These results are in Appendix Table A6.

6.3.1. Extensions to Alternative Cultural Proxies

In the Appendix, we also present evidence examining uncertainty avoidance (UAI), another one of Hofstede's cultural measures. While Hofstede identified six different dimensions of societal culture, our primary focus has been on individualism and power distance because they generate contrasting theoretical insights. However, it is plausible that uncertainty avoidance could also shift the marginal cost of withdrawal and follow a nearly identical mechanism as that posited for power distance.

Intuitively, for users from high uncertainty avoidance cultures, withdrawing requires irreversible on-chain actions, so these users would overweight the risk of acting during the confusing pre-collapse period relative to the risk of the Celsius platform's state. That is, the users would prefer to wait until unambiguous evidence arrives about Celsius. Because the Celsius leaders and regulators had yet to describe the state of Celsius accurately, these users would have an elevated perceived cost of acting when the situation was unclear, despite more traditional information signals indicating that action was warranted. To test this additional hypothesis, we repeat our analysis, focusing on uncertainty avoidance. We find patterns consistent with high uncertainty avoidance cultures acting like high power distance cultures for the intensive and extensive margins of withdrawal, albeit to a lesser extent than power distance when all measures are combined in a regression. We also find evidence that uncertainty avoidance significantly mediates users' responses to traditional information signals. These results are in Appendix Table A7 and Table A9.

Finally, following prior research Porta et al. (1997); Guiso et al. (2008); Pevzner et al. (2015), we proxy for societal trust using the average citizens' response on the World Values Survey to a variant of a question of generalized trust.[7]. Trust by itself does not consistently and significantly enter as a determinant of withdrawals. However, when we control for Hofstede's six cultural dimensions, demographic, and depositor account characteristics, we find some evidence consistent with greater generalized trust being correlated with having stranded assets and higher stranded asset ratios. Importantly, we observe no change in the sign or significance for any of the cultural heritage measures predicted by our model. For comparison, the economic magnitude on individuals is 2.6x larger than that of trust. These results are in Appendix Table A8.

Our analysis of user withdrawals before the halting of withdrawals suggests that even in

[7]This survey is conducted in waves, and the most recent wave (7) ended right before the Celsius collapse. We, therefore, use measures from this wave, and if a country did not participate, we use the wave before that. The generalized trust question (i.e., trust toward generic members of the population in your own country) was not part of this wave. But a more general version of the question, people you meet for the first time was asked, which we use.

the crypto space, bank-like entities can experience runs that are not purely informational phenomena. Instead, depositors interpret signals through a cultural lens, with traits such as individualism or power distance systematically moderating responsiveness. The implications are twofold. First, fragility channels may be stronger in institutions whose depositor base comes from cultural contexts that amplify the impact of negative signals. Second, the effectiveness of crisis communications or regulatory interventions may depend on the cultural composition of depositors. This highlights the importance of incorporating cultural heterogeneity into our understanding of financial fragility (Guiso et al., 2006).

6.4. Stranded Assets and Wallet Transactions and Holdings

Before turning to our analysis of subsequent trading activity and wallet composition in relation to demographic and cultural variables, it is essential to note that these empirical tests rely on a subsample of wallets for which we can reverse-engineer the names associated with transactions to actual addresses. Therefore, we compare how that subsample differs from the more comprehensive sample. As reported in Table A10 and Table A11, the forensically matched sample differs in several dimensions. Furthermore, those with and without stranded assets also differ from each other. Despite these differences, we do know that they appear to follow parallel trends, which is one of the main assumptions to satisfy for identification purposes.

Table 7 presents the results of a regression analysis examining the relation between *Post* $\times$ *Treat* and wallet transactions. The table includes four different regression models with the following dependent variables: the total number of transactions (Column 1), the number of Send/Receive transactions (Column 2), the number of lower-risk token transactions (Column 3) and higher-risk token transactions (Column 4). We define total transactions broadly to encompass all on-chain wallet activity, including cryptocurrency transfers (sent and received), NFT transactions, and smart contract interactions. We use the specification in Eq. 1.

[Insert Table 7 here]

In Column 1, the coefficient on *Post* × *Treat* is negative (-0.028) and statistically significant at the 99th percentile, indicating that wallets of Celsius users with stranded assets decrease the number of transactions after having withdrawals halted. Similarly, we observe a decrease in *Send/Receive* transactions, where the coefficient on the interaction term is -0.024 and statistically significant at the 99th percentile. Send/receive focuses solely on cryptocurrency transfers rather than interactions with DeFi protocols and smart contracts. While overall transactions and transfers decrease, when we examine the risk of these transfers, we see that the reduction is concentrated in lower-risk tokens, including market-dominant names such as Ethereum and Bitcoin, whereas we see no change in high-risk tokens.

Having established how users with stranded assets altered their transaction patterns and token choices for buying and selling, a natural question is how these changes manifested in their overall wallet composition and risk exposure. To investigate this, we examine various wallet-level metrics associated with our three potential mechanisms: gambling-for-resurrection, flight-to-quality, and limited attention.

[Insert Table 8 here]

Specifically, Table 8 presents DiD estimates examining how being unable to completely withdraw assets from Celsius is linked to subsequent wallet composition and risk-taking behavior. First, in Column 1, we observe that these investors exhibit significantly higher weekly returns of 2.4 percent, which are statistically significant at the 99th percentile. This return pattern appears to occur because holders move away from market-cap dominant tokens (e.g., Bitcoin, Ethereum, and Polygon) and instead shift their assets from stablecoins and even medium-risk tokens to high-risk tokens. Specifically, we observe a 2 p.p. reduction in stablecoins and an 8 p.p. reduction in medium-risk tokens. At the same time, we find a 4 p.p. increase in their allocation to high-risk tokens.

This pattern suggests that the experience of having assets trapped at Celsius fundamentally alters investor behavior, leading to increased risk-seeking. These actions are more consistent with the gambling-for-resurrection rather than the flight-to-quality mechanism.

The combination of higher returns alongside increased exposure to high-risk tokens suggests that these investors are not becoming more conservative, but are instead pursuing more aggressive strategies, possibly reflecting either a desire to recover losses quickly or a changed perception of risk following their experience with centralized platform failures.

To further explore the mechanisms posited by behavioral finance theory, we examine two additional aspects. First, we explore limited attention in the aftermath of the collapse. Consistent with retail investors' reliance on salient cues rather than full screening, we observe that individual investors allocate to high-momentum, attention-grabbing assets. We also observe bursty trading, defined as the concentration of an investor's trades into short, tightly clustered episodes separated by long periods of inactivity. Thus, there appears to be evidence for both limited attention and gambling-for-resurrection.

Second, in Table 9 we examine whether post-collapse portfolio adjustments vary systematically with realized loss severity. Across the three behavioral mechanisms we consider, the clearest patterns arise on the risk-taking margin. Users who experienced larger realized losses rebalance into more concentrated portfolios and reduce their holdings of market-cap–dominant tokens, consistent with narrowly targeted forms of loss-induced risk escalation associated with reference-dependent models. In contrast, we find little evidence that loss severity amplifies precautionary shifts toward stablecoins or dominant assets, nor does it meaningfully increase trading intensity or attention-driven bursts. Thus, while losses do not generate broad changes across all behavioral channels, they do help distinguish among the competing mechanisms. Loss severity predicts modest but theoretically consistent increases in risk concentration, which is consistent with gambling-for-resurrection, but not flight-to-quality or limited-attention responses that alternative frameworks would imply.

[Insert Table 9 here]

6.5. Robustness

We also implement an alternative fuzzy regression discontinuity design (FRDD) that exploits the cutoff in the timing of the withdrawal freeze as an independent source of identification. Some depositors attempted to withdraw assets from their Earn account after the deadline, but their requests were denied as depicted in appxfig:RDD. We follow standard practices in the literature to implement bandwidth selectors for local polynomial regressions. We use the optimal mean-square error (MSE) bandwidths and evaluate both the recommended symmetric and asymmetric bias-corrected bandwidths around the freezing threshold. The benefit of RD estimates is that they are internally valid under standard continuity assumptions, which we establish by showing the smoothness of predetermined covariates and pre-outcomes around the cutoff and by showing no evidence of manipulation of the forcing variable or spurious discontinuities at placebo thresholds.

Our estimates show that the resulting local treatment effects are statistically and economically similar to our baseline DiD estimates, providing a sanity check that the main results are not an artifact of functional form, differential trends, or broader sample composition. This is especially helpful in ensuring concerns that being left with stranded assets was not part of a sunspot run, but in fact predictable by fundamentals. This test exploits the timing in a close window near the freezing threshold.

6.6. Cultural Determinants of Wallet Transactions

Next, we examine the hypothesis that users with stranded assets experienced a culture-specific response to the collapse. Table 10 displays the coefficient estimates for users in the bottom quartile of a cultural element in Panel A and the estimates for users in the upper quartile of culture in Panel B. We examine the same cultural elements that were predicted to mediate or amplify responses to traditional information signals, leaving users with more or less stranded assets. Comparing users with low versus high cultural backgrounds, conditional on being treated, enables us to understand differential responses better.

In Columns 1–2, we again examine send/receive transactions to focus on the direct activity of the user rather than smart contract interactions. Then, in Columns 3–4, we examine transactions in low-risk tokens, while in Columns 5–6, we examine high-risk tokens. We find that both elements of culture predicted by the theory to mediate (power distance) and amplify responses (individualism) before collapse have meaningful relations with subsequent wallet transactions and holdings.

Specifically, we find that users in the bottom quartile of individualism with stranded assets transact more frequently (Column 1) and are more likely to rebalance into safer assets (Column 3), while those in the top quartile with stranded assets transact less regularly and are less likely to transact in low-risk tokens. In three out of four specifications, the estimates are significant at the 5% level, and one is significant at 10% level. This quieter on-chain activity among those with high individualism suggests that they are less inclined to execute routine cleanup trades and do not systematically add to safe assets in the post-period.

In contrast, those from high power distance societies have the opposite reaction to those from high individualism societies. The top quartile of users from high power-distance societies increases their on-chain activity (Column 2) and is more likely to transact in low-risk tokens after the collapse (Column 4). Whereas those from low-power-distance societies tend to reduce trading and the use of low-risk tokens. The absence of systematic high-risk buying in any group aligns with the notion that post-collapse reallocation among the stranded is primarily about risk containment, not speculation.

This pattern and style of portfolio repair among those with stranded assets is consistent with two complementary channels. First, selection implies that many high-individualism investors had already exited before the withdrawals were halted, so the high-individualism investors who remain exposed are precisely those likely to follow their individual beliefs and not follow the rest of the community by engaging in routine stabilization trades post-collapse. In contrast, those who are not individualistic societies do appear to rely on community information and standardized responses in the aftermath of failure (more trading and movements

to lower-risk tokens). The second channel is an authority re-anchoring channel. Before the freeze, high power distance users were slower to withdraw and thus ended up with more stranded assets. After the freeze, they seek better authority and focus on lower-risk tokens like stablecoins as their design reduces their volatility by pegging them to the safety of traditional authority.

[Insert Table 10 here]

In Appendix Table A12, we relax the assumption that culture works through stranded assets and allow for a more general cultural reaction post-collapse. The results indicate a similar general pattern of post-collapse adjustment, differing in how individualistic or deferential a user is to authority. The results are significant in 6 out of 12 specifications, including both for power distance and high-risk tokens. Taken together, this suggests that the cultural sensitivity that can influence trading volume works through both the collapse itself and the realized outcome of having stranded assets.

Finally, as before, we repeat this exercise for Hofstede's cultural element of uncertainty avoidance, which works through a similar mechanism to power distance. Given that high uncertainty avoidance is associated with more stranded assets and shifting the threshold to act before the withdrawal freeze, we want to understand if, after the shock, there are the same culturally distinct post-collapse adjustments. Appendix Table A13 shows the findings for the bottom quartile and upper quartile of uncertainty avoidance users who had stranded assets after the collapse. Consistent with the patterns for power distance, we find that uncertainty avoidance shapes the style of portfolio repair among those with stranded assets primarily through sending and receiving transactions and shifts toward low-risk tokens.

7. Policy Discussion

Our setting is a crypto shadow bank, where insiders privately sold while making reassuring public appearances. The particulars are novel, but the underlying formal and informal

monitoring mechanisms that we uncover are not. We find that depositor monitoring is shaped by identity, captured in our setting by Hofstede's power distance and individualism. But identity is a broader concept – it can be cultural, ethnic, professional, or sectoral. The key is that identity alters preferences in ways standard models often reserve for information or payoffs (Akerlof and Kranton, 2000). By deriving how culture may alter withdrawal behavior, as we did, we can turn to empirically testing the efficacy of such predictions.

Importantly, we show empirically that identity can be a double-edged sword in this depository setting. A depositor base with a common identity can be an asset ex ante. It lowers acquisition costs, speeds information diffusion, and coordinates support in regular times. Yet, the same force becomes a liability in times of stress. When public reassurances conflict with facts, depositors' revisions of their beliefs tend to synchronize within identity groups. In our setting, we observed this with individualism, which allowed users from those societies to exit earlier and more quickly. This resulted in an identity-conditioned amplification of the Celsius run.

In settings outside of crypto, episodes with concentrated depositor identities exhibit similar dynamics. Historical community and immigrant-focused banks in New York, most prominently the Bank of the United States in 1930, relied on strong within-group ties that stabilized funding in normal times yet synchronized withdrawal thresholds in times of stress (Calomiris, 2012). More recently, this same phenomenon occurred in the late 2000s at Abacus Bank, a family-run bank in New York City (James, 2016). Thus, this phenomenon is not limited to unsophisticated immigrant borrowers or historical periods. Instead, our evidence is consistent with this type of identity-conditioned depositor base amplifying runs more generally. In fact, a professional identity analogue appears in the case of Silicon Valley Bank. In that case, we observed dense depositor networks composed of venture capitalists and startup financial officers amplify a coordinated and synchronized response (Cookson et al., 2023; Choi et al., 2024; Jiang et al., 2024).

Taken together with our crypto evidence, three policy implications follow. First, banking

regulators and executives should evaluate identity concentration as a potential risk factor. Second, in settings where identity concentration is high, tools to improve the credibility of traditional information signals should be sought rather than corrective actions (Schilling, 2023). For example, regulators could encourage auditable disclosure of insider actions even in digital asset settings. Having clear, rule-based information about insiders' actions could reduce cheap-talk equilibria, which would have been especially valuable in settings like ours, where users were hurt. Third, digital-asset platforms with predominantly retail users, as was the case in our setting, warrant proportionate consumer protection measures, such as verifiable segregation/attestation of custodial assets. These measures could have helped to reduce the risk concentration growing among younger, smaller banks (Eisenbach et al., 2022). These recommendations follow naturally from both our specific investigation of a crypto platform failure and our broader, technology-agnostic point that fragility can and does stem from the interaction of leadership credibility, information intermediation, and depositor identity.

8. Conclusion

This study provides new evidence on how both economic incentives and cultural norms shape depositor behavior in distressed shadow banks. Using quasi-exogenous variation stemming from the collapse of Celsius, and linking blockchain addresses to individual demographics and cultural characteristics through bankruptcy filings, we show that depositor responses to crisis were not uniform. Monitoring forces were important. Users with larger holdings and institutional status were less likely to be left with stranded assets, and withdrawals responded strongly to informational signals such as news sentiment and insider transactions. Yet monitoring incentives and information alone cannot explain outcomes. Cultural heritage was also a key determinant of both who was left with stranded assets and how users adapted their portfolios after the freeze.

We find that users from more individualistic cultures withdrew funds earlier and more aggressively, leaving fewer stranded assets, while users from more hierarchical cultures that act deferentially to authority delayed withdrawals and incurred greater losses. Following the suspension of withdrawals, stranded assets shaped subsequent portfolio behavior. Users with larger stranded balances reduced overall transaction activity but reallocated their portfolios away from stablecoins and medium-risk tokens and toward higher-risk assets. This shift is consistent with gambling-for-resurrection mechanism rather than a flight-to-quality mechanism, which is further supported by tests examining the value of realized losses. Again, however, cultural differences conditioned these responses. Users from less individualistic cultures were more likely to increase their holdings of low-risk tokens, while those from less hierarchical societies cut back on safer assets.

Taken together, these findings highlight the role of both monitoring capacity and culture in shaping depositor behavior under stress. Monitoring and information access predict early withdrawals, but cultural norms amplify or dampen these responses. These results suggest that informal mechanisms, such as cultural identity, that shape depositor preferences should also be considered during periods of financial crisis and depositor runs. In settings where identity concentration is high and can become a liability to the depository institution, having policies that support the sharing of credible information would be welcome. More broadly, regulators and policymakers should consider how depositor identity concentration interacts with institutional design features in shaping the severity of runs, with an eye toward developing safeguards that mitigate fragility in both traditional and emerging financial systems.

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Fig. 1. **Celsius Network Business Model**

Celsius marketed its CEL token as the backbone of the entire platform, with CEO Alex Mashinsky repeatedly telling customers that CEL's value directly reflected the company's worth. In fact, CEL was described not just as another cryptocurrency but as the engine that would power a self-reinforcing business model, where company success, token value, and customer rewards would all grow in tandem. The steps in the flywheel business model are illustrated in the diagram below.



Fig. 2. **How Cultural Elements Shift Withdrawal Incentives**

This figure illustrates how cultural heritage shapes withdrawal incentives. The horizontal axis shows the withdrawal share y, and the vertical axis shows the marginal benefit or marginal cost of withdrawing one more unit. The upper panel shows the effect of individualism (IDV), and the lower panel shows power distance (PDI). When individualism is high, the perceived marginal benefit of withdrawing is greater (navy dashed line), so depositors act earlier and withdraw more. Conversely, low individualism (collectivism in Hofstede's terminology) lowers the marginal benefit (navy dotted line), so depositors delay and withdraw less. While individualism shifts the marginal benefit, power distance shifts the marginal cost. Depositors from high–power distance societies face a higher effective marginal cost of withdrawing (maroon dashed line), which makes them slower to act and less aggressive once they do. By contrast, low–power distance reduces this cost (maroon dotted line), leading depositors to trust their own signals more and withdraw both earlier and more fully.

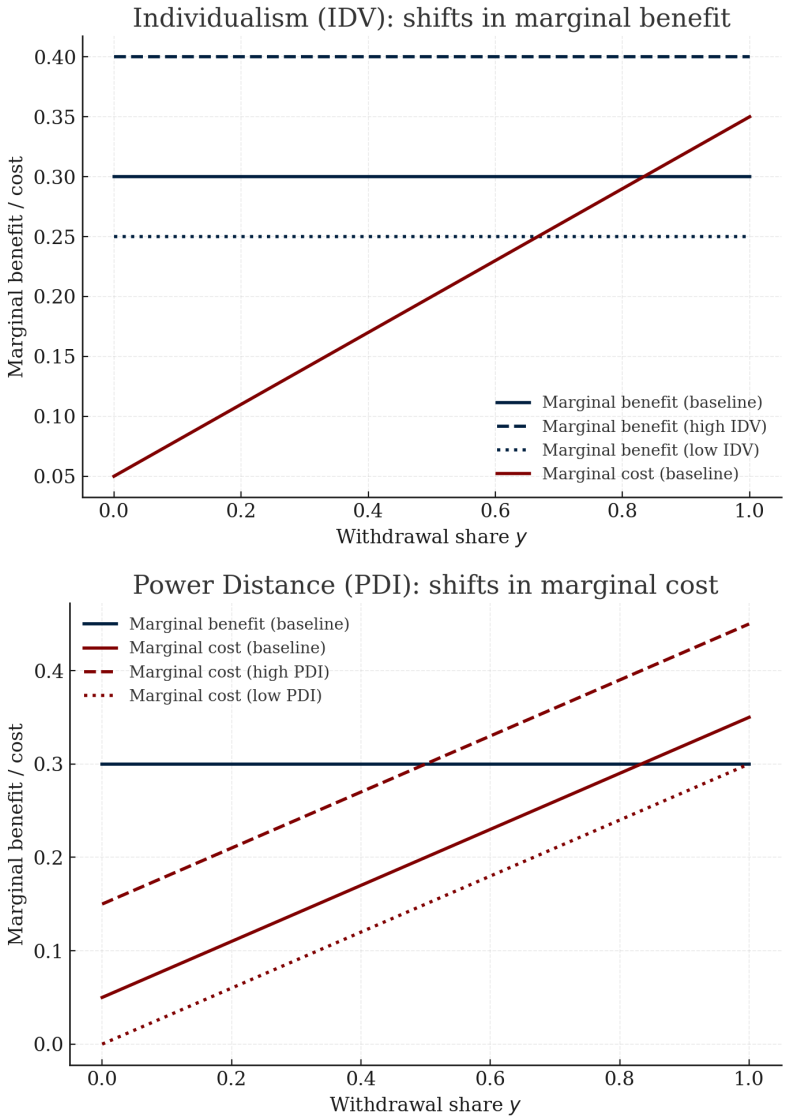


Fig. 3. **Earn Account Deposits and Withdrawals**

This figure illustrates the daily outgoing and incoming values of Earn Accounts for Celsius Networks over the period from April 12, 2022, to June 12, 2022. The y-axis represents the monetary values in millions of U.S. dollars, while the x-axis denotes the date. The blue line represents the outgoing value, indicating withdrawals from the Earn Accounts. The red line represents the incoming value, indicating deposits into the earn accounts.

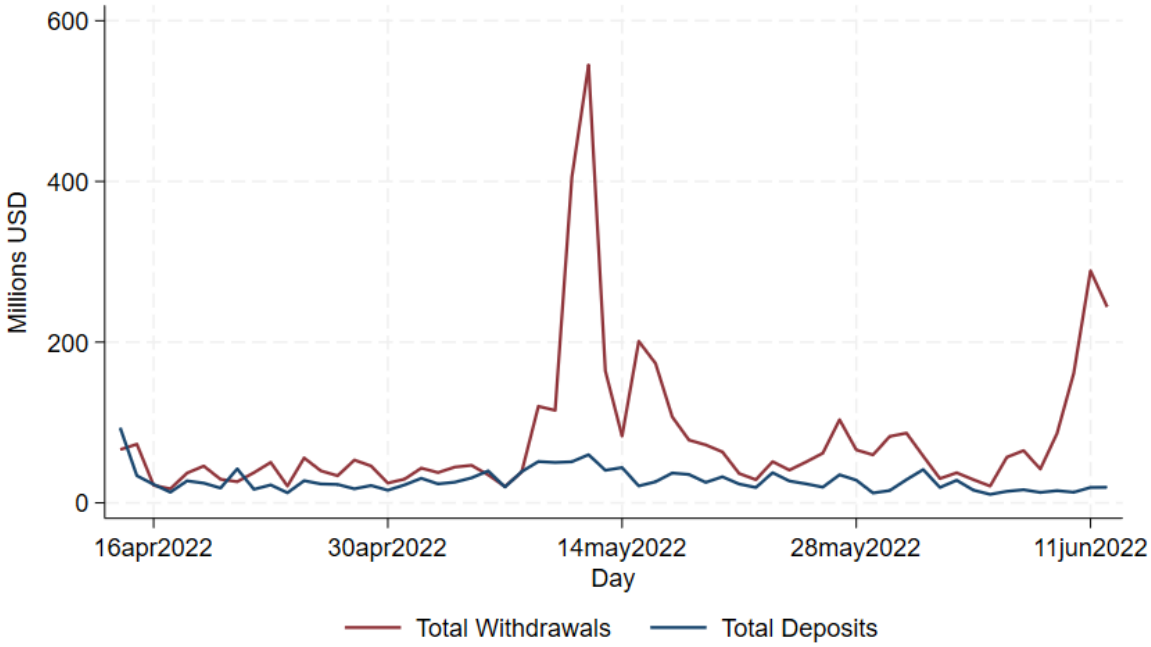


Fig. 4. **Earn Account Withdrawals by Users and Insiders**

This figure illustrates the daily withdrawals by Celsius users and insiders from the Celsius Networks over the period from April 12, 2022, to June 12, 2022. The two y-axes represent the withdrawal values in millions of U.S. dollars, while the x-axis denotes the date. The shaded grey area represents the period from the initial Terra-Luna depegging to the suspension of all trading.

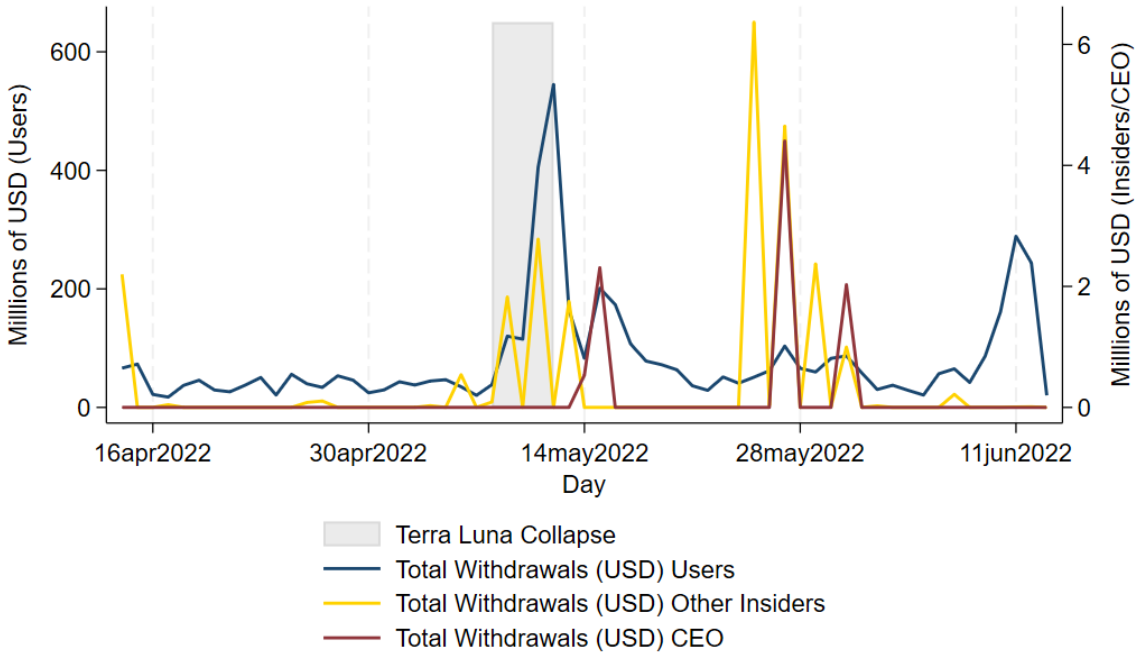


Fig. 5. **Test of Parallel Trends Around Celsius Collapse**

These figures present all weekly coefficient estimates from our parallel-trends analyses of users' complete wallet trades around Celsius's bankruptcy filing. Each point estimate represents the weekly difference in transaction type between wallets holding stranded assets and control wallets without such exposure. The pre-period coefficient estimates are placebo tests of parallel trends, while each post-period coefficient is a week-specific dynamic treatment effect. We account for users' exposure to Terra Luna in the pre-period by controlling for those users whose wallets either held or traded Terra or Luna in the 2022 calendar year. The top figure displays the estimates for trades in low-risk tokens, while the bottom figure illustrates the estimates for trades in high-risk tokens. Blue dots indicate coefficient estimates, and the bars show the corresponding confidence intervals. The p-values reported below the figure test the joint significance of pre-period coefficients and the stability of post-period treatment effects.

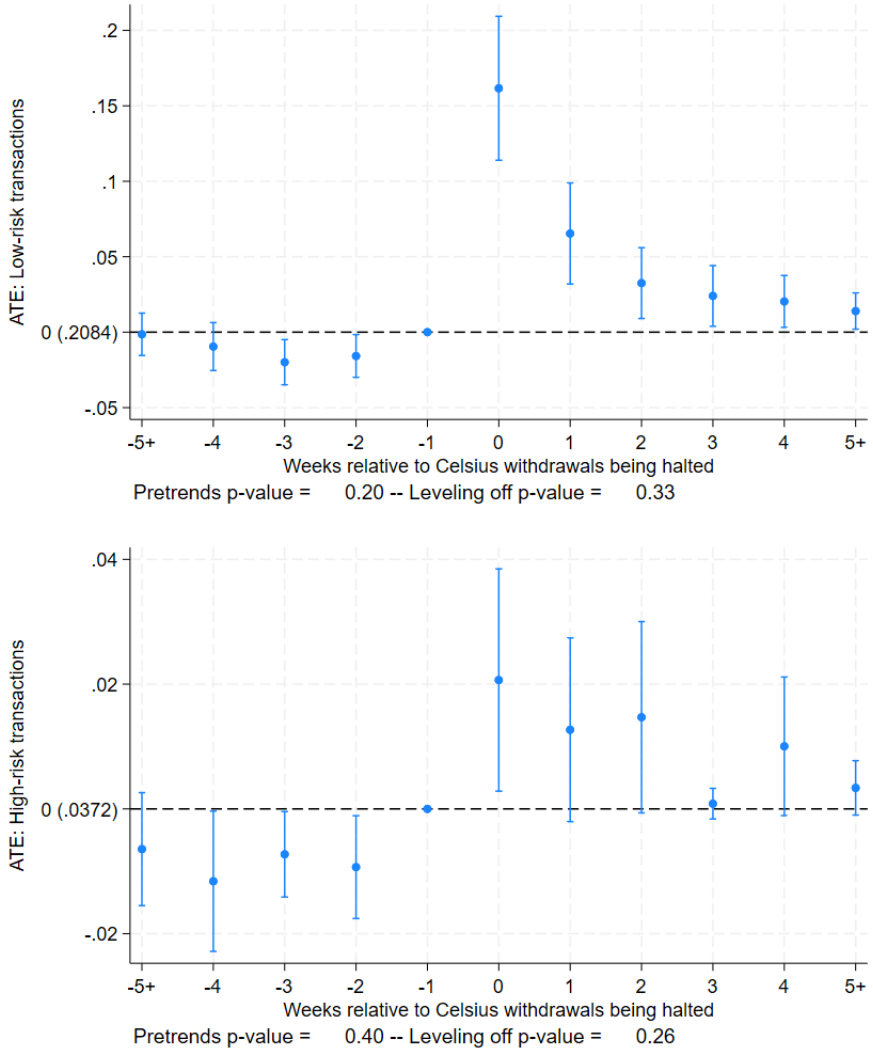


Fig. 6. **Earn Account Initial Holdings**

This chart illustrates the distribution of initial holdings in USD across Earn Accounts for Celsius Networks over the period from April 12, 2022, to June 12, 2022. The x-axis represents the initial holdings in increments of $10,000, extending to a category labeled "50,000+" for accounts with holdings greater than or equal to $50,000. The y-axis indicates the fraction of accounts corresponding to each range of initial holdings.

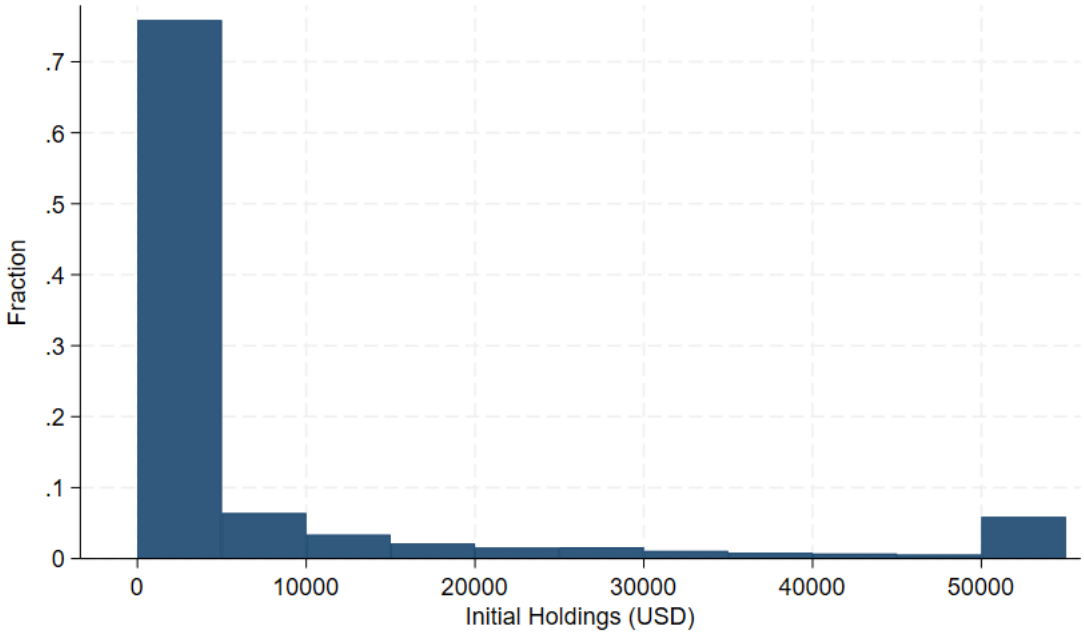


Table 1: **Celsius Depositor Demographics**

This table provides a breakdown of the demographics of depositors within the Celsius Network. The data are categorized by depositor type, gender, and ethnicity, providing an overview of the depositor base. The demographic characteristics and cultural heritage are derived from the names of bankruptcy filers and our multi-step algorithm, as described in Appendix A. The culture dimensions are well-established measures of national culture developed by Hofstede. We exclude institutions from the analysis of gender, ethnicity, and culture.

	Obs.	Pct.
Panel A. Depositor Type	(1)	(2)
Individuals	492,436	99.6
Institutions	492,436	0.4
Panel B. Depositor Gender		
Male	490,457	74.35
Female	490,457	19.77
Unknown	490,457	5.87
Panel C. Depositor Ethnicity		
Anglo-Saxon	490,457	26.50
German	490,457	12.65
Hispanic	490,457	9.31
French	490,457	9.53
Italian	490,457	9.23
Chinese	490,457	6.95
Indian	490,457	6.43
Russian	490,457	4.81
Arabic/Middle Eastern	490,457	3.43
African	490,457	2.34
Other/Unknown	490,457	8.79
Panel D. Depositor Cultural Heritage (Mean, 0-100)		
Power distance (PDI)	490,457	55.73
Individualism (IDV)	490,457	59.27
Uncertainty Avoidance (UAI)	490,457	62.16

Table 2: **Summary Statistics for Celsius Accounts**

This table presents the summary statistics for accounts held by Celsius Network users. Panel A describes the account types. Panels B through D focus on the Earn accounts (i.e., interest-bearing savings accounts) and are categorized as Token Holdings (Panel B), Transactions (Panel C), and Balances (Panel D). Each Panel provides detailed statistics, including the number of observations (N), mean, standard deviation (SD), and the 25th, 50th (median), and 75th, 95th, and 99th percentiles, respectively.

	Obs.	Mean	Std. Dev.	25%	50%	75%	95%	99%
Panel A. Account Types Used	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Earn account	492,429	1.00	0.06	1	1	1	1	1
Custody account	492,429	0.11	0.31	0	0	0	1	1
Withheld account	492,429	0.01	0.11	0	0	0	0	1
Panel B. Earn Account Token Holdings								
Number of tokens held	492,429	3.33	2.96	1	2	4	9	15
Holds Bitcoin indicator	492,429	0.71	0.45	0	1	1	1	1
Holds Ethereum indicator	492,429	0.42	0.49	0	0	1	1	1
Holds stablecoins indicator	492,429	0.27	0.45	0	0	1	1	1
Holds other tokens indicator	492,429	0.75	0.43	1	1	1	1	1
Panel C. Earn Account Transactions								
Number of incoming transactions	492,429	1	7	0	0	0	3	12
Incoming Bitcoin (USD)	492,429	1,761	59,302	0	0	0	717	28,308
Incoming Ethereum (USD)	492,429	1,368	90,004	0	0	0	134	15,690
Incoming stablecoins (USD)	492,429	1,372	82,417	0	0	0	0	11,437
Incoming other (USD)	492,429	1,238	58,573	0	0	0	389	11,933
Number of outgoing transactions	492,429	1	7	0	0	1	6	17
Outgoing Bitcoin (USD)	492,429	3,888	122,987	0	0	0	7,126	57,222
Outgoing Ethereum (USD)	492,429	3,004	126,982	0	0	0	3,665	48,965
Outgoing stablecoins (USD)	492,429	2,554	117,582	0	0	0	565	33,514
Outgoing other (USD)	492,429	2,299	93,349	0	0	0	1,743	27,248
Total interest earned (USD)	492,429	172	1,810	0	9	72	605	2,224
Interest earned from Bitcoin (USD)	492,429	36	369	0	0	17	167	467
Interest earned from Ethereum (USD)	492,429	42	718	0	0	2	147	658
Interest earned from stablecoins (USD)	492,429	35	787	0	0	0	46	628
Interest earned from other (USD)	492,429	60	1,126	0	0	8	148	833
Panel D. Earn Account Balances								
Initial holdings (USD)	492,429	18,606	278,832	5	354	4,542	58,923	258,730
Stranded asset ratio	492,429	0.83	0.35	1	1	1	1	1

Table 3: **Stranded Assets and Monitoring Incentives**

This table examines the relation between monitoring incentives and stranded assets on the intensive and extensive margin. The dependent variables in columns (1) through (2) are the stranded asset ratio, and in columns (3) through (4) are the stranded asset indicator. The independent variables include an institution indicator and initial Earn account holdings represented by the logarithm of 1 plus initial holdings. Columns (2) and (4) include additional controls for demographics and account use. Robust standard errors are reported in parentheses. For the probit regressions in Columns (3) and (4), the pseudo R-squared is reported. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Stranded asset ratio		Stranded asset indicator	
	(1)	(2)	(3)	(4)
Institution indicator	-0.033***	-0.043***	-0.045	-0.084**
	(0.010)	(0.010)	(0.032)	(0.033)
Initial Earn account holdings (USD)	-0.031***	-0.027***	-0.124***	-0.115***
	(0.000)	(0.000)	(0.001)	(0.001)
Controls	No	Yes	No	Yes
Observations	492,429	492,429	492,429	492,429
R-squared	0.106	0.116	0.094	0.102

Table 4: **Users Withdrawals in Response to Informational Signals Weekly**

This table examines the relation between traditional informational signals and users' decisions to make withdrawals from Celsius. In columns (1) and (2), the dependent variable indicates whether a user withdrew from their Earn account, and in columns (3) and (4), it represents the user's normalized withdrawal amount from their Earn account. All specifications include user fixed effects, and robust standard errors clustered by user and week are reported in parentheses. Even columns drop observations during the Terra Luna collapse, and odd columns include an indicator variable for the Terra Luna collapse time period. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Withdrawal indicator		Withdrawal amount	
	(1)	(2)	(3)	(4)
Celsius news sentiment	-0.032***	-0.032***	-0.030***	-0.030***
	(0.005)	(0.005)	(0.005)	(0.005)
CEL returns	-0.005*	-0.005*	-0.005*	-0.005*
	(0.003)	(0.003)	(0.002)	(0.002)
CEL volume	-0.019***	-0.019***	-0.015***	-0.015***
	(0.004)	(0.004)	(0.003)	(0.003)
Insider withdrawal indicator	0.043***	0.043***	0.026***	0.026***
	(0.006)	(0.006)	(0.005)	(0.005)
User fixed effects	Yes	Yes	Yes	Yes
Terra Luna controls	Yes	No	Yes	No
Drop Terra Luna observations	No	Yes	No	Yes
Observations	6,620,004	6,068,281	6,620,004	6,068,281
R-squared	0.185	0.183	0.166	0.156

Table 5: **Stranded Assets and Cultural Heritage**

This table examines the relation between Celsius depositor cultural heritage on the intensive and extensive margin. The dependent variables in columns (1) through (3) are the stranded asset ratio, and in columns (4) through (6) are the stranded asset indicator. While we include controls for all of Hofstede's six cultural elements in Columns (3) and (6), we focus on those that our theoretical framework posits as most important. For the probit regressions in Columns (4) through (6), the pseudo R-squared is reported. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Stranded asset ratio			Stranded asset indicator		
	(1)	(2)	(3)	(4)	(5)	(6)
Individualism (IDV)	-0.003***		-0.025***	-0.008***		-0.103***
	(0.001)		(0.004)	(0.002)		(0.018)
Power distance (PDI)		0.002***	0.008***		0.001	0.020**
		(0.001)	(0.002)		(0.002)	(0.010)
Controls	No	No	Yes	No	No	Yes
Observations	492,429	492,429	492,429	492,429	492,429	492,429
R-squared	0.001	0.001	0.001	0.062	0.001	0.001

Table 6: **Cultural Sensitivity to Traditional Information Signals**

This table explores whether elements of cultural heritage can amplify or mediate the response to traditional informational signals before Celsius officially halted withdrawals. In all columns, the dependent variable is the user's normalized withdrawal amount from their Earn account. All specifications include user-fixed effects, and robust standard errors clustered by user and week are reported in parentheses. Across the columns, we vary Hofstede's cultural elements. In columns (1) and (2), we focus on Individualism, the cultural element posited to amplify reactions, and in columns (3) and (4), we focus on Power Distance, the cultural element posited to mediate reactions. Even columns drop observations during the Terra Luna collapse, and odd columns include an indicator variable for the Terra Luna collapse time period. Additional explanatory variables, including market signals of price and volume, as well as their respective interaction terms, are included but not displayed for brevity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dep. var. = Withdrawal amount			
	Amplifying reaction Individualism (IDV)		Mediating reaction Power distance (PDI)	
	(1)	(2)	(3)	(4)
Celsius news sentiment	-0.026***	-0.027***	-0.050***	-0.050***
	(0.004)	(0.005)	(0.008)	(0.008)
CEL news sentiment × culture	-0.003**	-0.003**	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
CEL insider withdrawal indicator	0.027***	0.026***	0.042***	0.042***
	(0.005)	(0.005)	(0.008)	(0.008)
CEL insider withdrawal × culture	0.001	0.001*	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Additional explanatory variables	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes
Terra Luna controls	Yes	No	Yes	No
Drop Terra Luna observations	No	Yes	No	Yes
Observations	5,909,148	5,416,719	5,909,148	5,416,719
R-squared	0.165	0.155	0.165	0.155

Table 7: **Stranded Assets and Wallet Transactions**

This table examines the relation between wallet transactions and the presence of stranded assets after withdrawals were halted at Celsius. The dependent variables are the total number of transactions (column 1), the total number of transactions categorized as send or receive to exclude smart contract and bot activity (column 2), transactions involving low-risk tokens (column 3), and transactions involving high-risk tokens (Column 4). The variable *Post* equals 1 if the week is on or after June 12-18, 2022, which is the date withdrawals were halted on Celsius. The variable *Treat* equals 1 if the user has stranded assets, which are computed as the amount of initial holdings plus deposits minus withdrawals, in US dollars. The variable of interest is *Post* × *Treat*. The specification follows that outlined in Eq. (2). The data encompasses the 20 weeks surrounding the withdrawal halt. The last day in the sample is September 6, 2022. There are 31,293 unique wallets in the sample. Terra Luna controls account for how treatment may vary by Terra-Luna exposure. All regressions use ordinary least squares with wallet and week fixed effects. Robust standard errors, clustered by wallet, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Transaction types		Token risk	
	Number of transactions	Send/receive transactions	Low-risk tokens	High-risk tokens
	(1)	(2)	(3)	(4)
Post × Treat	-0.028***	-0.024***	-0.014***	-0.000
	(0.008)	(0.007)	(0.002)	(0.000)
Terra Luna controls	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Observations	625,860	625,860	625,860	625,860
R-squared	0.191	0.186	0.152	0.087

Table 8: **Users Behavioral Responses to Stranded Assets**

This table examines the relation between having stranded assets after Celsius halted withdrawals and the three behavioral mechanisms predicted by theory. Columns 1–3 report dependent variables associated with the gambling-for-resurrection mechanism; columns 4–5 report outcomes corresponding to flight-to-quality; and columns 6–7 report outcomes tied to limited-attention behavior. The dependent variables are weekly returns (column 1), percent of the wallet allocated to high-risk tokens (column 2), wallet concentration (column 3), percent allocated to market-cap-dominant tokens (column 4), percent allocated to stablecoins (column 5), percent allocated to high-momentum tokens (column 6), and trade burstiness (column 7). The variable post equals 1 if the day is on or after June 12, 2022, which is the date withdrawals were halted. The variable stranded asset indicator equals 1 if the user has stranded assets, which are computed as the number of initial holdings plus deposits minus withdrawals, in US dollars. The variable of interest is Post × Treat and all regressions following the specification in Eq. (2). All regressions use ordinary least squares with wallet and week fixed effects. The individuals represent the 19,224 unique wallet addresses that we could reverse-engineer and match to user names and pull their full wallet holdings. The sample period spans the 20 weeks surrounding the collapse. Robust standard errors, clustered by wallet, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable =						
	Gambling-for-resurrection			Flight-to-quality		Limited-attention	
	Weekly return	% high risk	Wallet HHI	%mkt.-cap. dominant	% stablecoin	% high momentum	Trade bursts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post × Treat	0.024***	0.037***	0.089***	-0.168***	-0.021**	0.036**	0.065***
	(0.008)	(0.010)	(0.013)	(0.020)	(0.011)	(0.017)	(0.017)
Terra-Luna controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	384,106	384,106	384,106	384,106	384,106	384,106	384,106
R-squared	0.089	0.809	0.707	0.698	0.733	0.533	0.586

Table 9: **Severity of Losses and Users Behavioral Responses to Stranded Assets**

This table examines how post-collapse portfolio behavior varies with loss severity among users with stranded assets after Celsius halted withdrawals. Columns 1–3 report dependent variables associated with the gambling-for-resurrection mechanism; columns 4–5 report outcomes corresponding to flight-to-quality; and columns 6–7 report outcomes tied to limited-attention behavior. The dependent variables are weekly returns (column 1), percent of the wallet allocated to high-risk tokens (column 2), wallet concentration (column 3), percent allocated to market-cap-dominant tokens (column 4), percent allocated to stablecoins (column 5), percent allocated to high-momentum tokens (column 6), and trade burstiness (column 7). The variable post equals 1 if the day is on or after June 12, 2022, which is the date withdrawals were halted. The table reports the coefficients on $Post \times Treat$ and $Post \times Treat \times RealizedLoss$, where $RealizedLoss$ is the z-score of the user's percentage loss realized at the time of the freeze. All regressions use ordinary least squares with wallet and week fixed effects. The individuals represent the 19,224 unique wallet addresses that we could reverse-engineer and match to user names and pull their full wallet holdings. The sample period spans the 20 weeks surrounding the collapse. Robust standard errors, clustered by wallet, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable =						
	Gambling-for-resurrection			Flight-to-quality		Limited-attention	
	Weekly return	% high risk	Wallet HHI	%mkt.-cap. dominant	% stablecoin	% high momentum	Trade bursts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post × Treat	0.024***	0.037***	0.089***	-0.168***	-0.021**	0.036**	0.065***
	(0.008)	(0.010)	(0.013)	(0.020)	(0.011)	(0.017)	(0.017)
Post × RealizedLoss	-0.000	0.001	0.007***	-0.011***	-0.000	-0.001	-0.005
	(0.002)	(0.001)	(0.003)	(0.004)	(0.001)	(0.005)	(0.005)
Terra-Luna controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	384,106	384,106	384,106	384,106	384,106	384,106	384,106
R-squared	0.089	0.809	0.707	0.698	0.733	0.533	0.586

Table 10: **Wallet Transactions and Cultural Sensitivity to Stranded Assets**

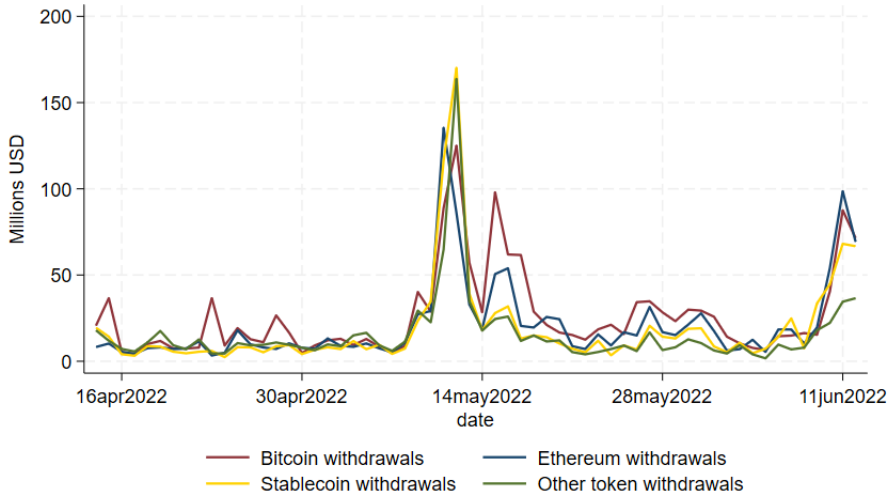
This table explores whether elements of cultural heritage can alter trading volume in the presence of stranded assets after withdrawals were halted at Celsius. In all Panels, the dependent variables are the total number of transactions, categorized as either send or receive transactions to remove smart contract and bot activity (columns 1-2), transactions in low-risk tokens (columns 3-4), transactions in high-risk tokens (columns 5-6). We use the triple-differences specification from Eq. (3). In Panel A, the focal variable is the triple interaction which uses an indicator for low culture (Q1) interacted with $Post \times Treat$. In Panel B, the focal variable is an indicator for high culture (Q4) interacted with $Post \times Treat$. Quartiles are computed from the sample distribution of the depositor-level cultural index, which is mapped from Hofstede's measures. All regressions use ordinary least squares with wallet and week fixed effects. Robust standard errors, clustered by wallet, are reported in parentheses. For brevity, additional explanatory variables are omitted from the table. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Send/receive transactions		Low risk tokens		High risk tokens	
	Indi-vidualism (IDV)	Power distance (PDI)	Indi-vidualism (IDV)	Power distance (PDI)	Indi-vidualism (IDV)	Power distance (PDI)
Panel A. Low culture	(1)	(2)	(3)	(4)	(5)	(6)
1{Culture $\leq Q1$}$\times$ Post $\times$ Treat	0.037**	-0.028**	0.008*	-0.006*	0.000	0.000
	(0.014)	(0.013)	(0.004)	(0.003)	(0.001)	(0.001)
Panel B. High culture						
1{Culture $\geq Q4$}$\times$ Post $\times$ Treat	-0.029**	0.026*	-0.009**	0.008**	-0.000	0.000
	(0.014)	(0.015)	(0.003)	(0.004)	(0.000)	(0.000)
Terra-Luna controls	Yes	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	625,166	625,166	625,166	625,166	625,166	625,166
R-squared	0.186	0.186	0.152	0.152	0.087	0.087

Fig. A1. **Earn Account Deposits and Withdrawals By Token**

This figure plots daily transaction activity for different types of tokens in Celsius Network Earn Accounts over the period April 14, 2022, to June 12, 2022. Panel A shows the outgoing values (withdrawals) for four types of tokens: Bitcoin (BTC), Ethereum (ETH), USD Coin (USDC), and Alternative Tokens (ALT). Panel B displays the incoming values (deposits) for the same four types of tokens. In both graphs, the y-axis represents the value of withdrawals or deposits in millions of USD, while the x-axis represents the date.

Panel A: Withdrawals



Panel B: Deposits

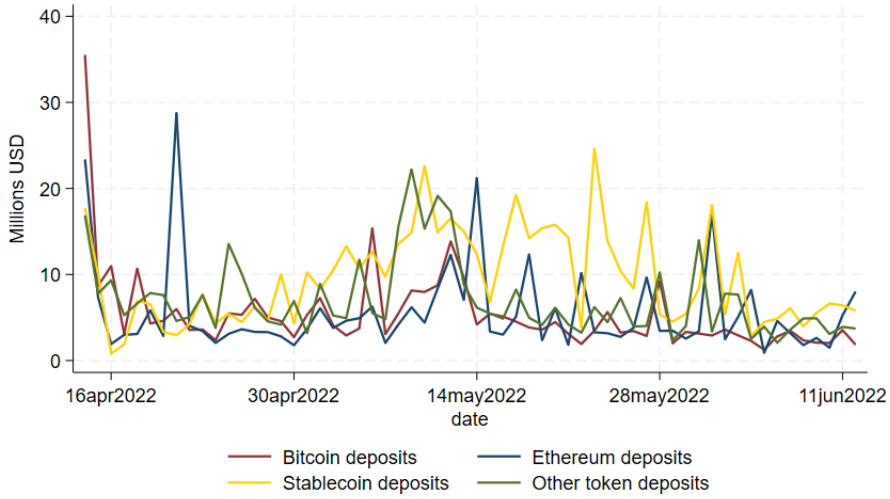


Fig. A2. **Wallet Transaction Volume Relative to Celsius Collapse**

This figure illustrates the total daily volume of transactions for our matched subsample of wallets associated with names listed in the Celsius bankruptcy filings. We define transactions broadly to encompass all on-chain wallet activity, including cryptocurrency transfers (sent and received), NFT transactions, and smart contract interactions. The figure plots the 10 weeks before and after the Celsius withdrawals being halted. The y-axis represents the total transactions, while the x-axis denotes the week relative to June 12, 2022, when Celsius halted all withdrawals. The navy line represents those who did not have assets stranded, and the dashed maroon line those with stranded assets that they were unable to withdraw from Celsius.

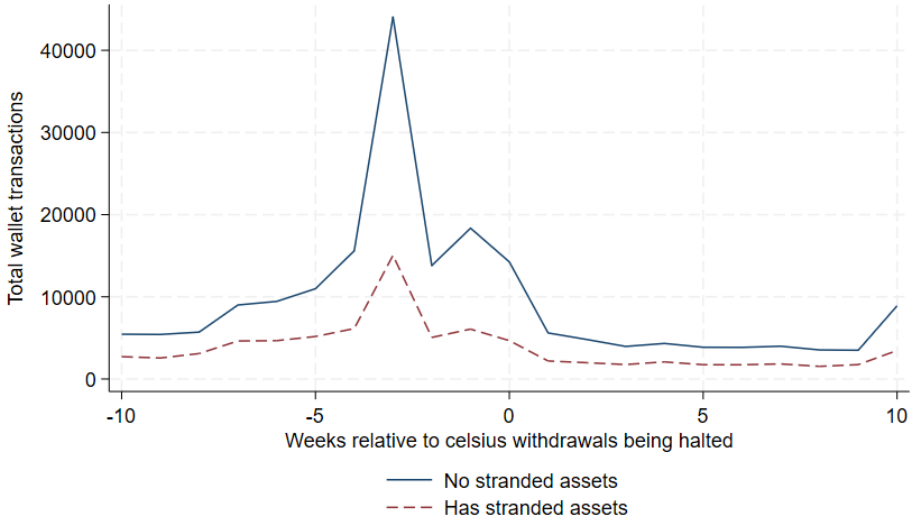


Fig. A3. **Timeline of Successful and Attempted Withdrawals Around the Freeze Cutoff**

This figure plots the daily number of user-initiated withdrawals (blue bars) and attempted withdrawals that were rejected due to the account freeze (red bars) surrounding the discontinuity date indicated by the vertical line. The sharp decline in successful withdrawals and the simultaneous emergence of failed attempts on the cutoff date illustrate the first-stage discontinuity that underpins our fuzzy regression discontinuity design. The running variable is calendar time, measured in days, and treatment assignment shifts discretely at the freeze. The figure highlights both the intensity of pre-freeze outflows and the abrupt mechanical break in withdrawal feasibility that generates quasi-experimental variation in subsequent portfolio behavior.

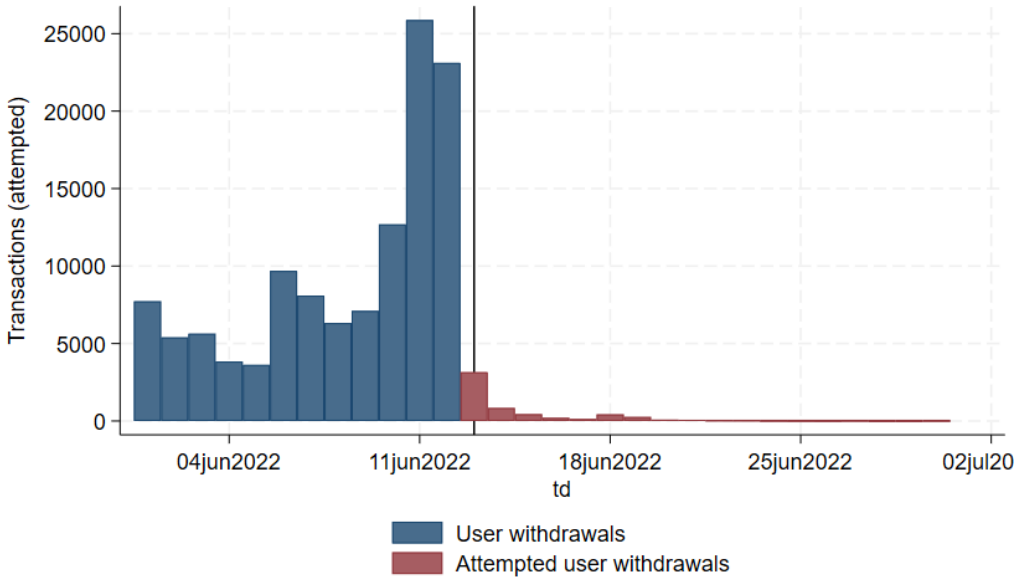


Table A1: **Institution Locations**

This table shows the geographic distribution of institutional users in the Celsius Network bankruptcy filings. We list the country, number of entities, and their percentage of all institutions in the sample.

Country	Entities	Percent
(1)	(2)	(3)
United States	1,174	58.76
Australia	491	24.57
Canada	99	4.95
United Kingdom	40	2.00
Hong Kong	23	1.15
Cayman Islands	22	1.10
Virgin Islands (British)	17	0.85
Singapore	16	0.80
Puerto Rico	13	0.65
South Africa	11	0.55
New Zealand	6	0.30
Seychelles	6	0.30
40 other countries	80	4.00

Table A2: **Aggregate Celsius Transactions by Token**

This table description provides descriptive statistics for transactions on Celsius Network by token. It lists various cryptocurrencies traded on the Celsius platform, along with the number of transactions and the total transaction value in millions of US dollars. The table lists 20 specific tokens along with a category for 40 other tokens.

Token (1)	Number of transactions (2)	Transaction value (USD millions) (3)
BTC	771,281	4817.91
ETH	465,142	4199.02
USDC	423,846	3307.29
CEL	295,180	257.50
MATIC	141,585	241.71
ADA	126,765	330.40
DOT	86,563	59.58
USDT	86,280	669.85
LINK	70,484	158.99
SOL	59,945	128.21
LTC	59,850	38.79
XLM	49,890	14.69
SNX	49,400	22.92
AVAX	40,911	42.32
XRP	32,691	55.36
LUNC	27,919	44.40
MCDAI	27,660	32.32
BNB	25,237	35.79
BCH	24,990	21.15
AAVE	24,719	16.00
40 Other tokens	270,652	739.02

Table A3: **Stranded Assets and Depositor Demographics**

This table examines the relation between Celsius depositor demographic characteristics and the intensive and extensive margins of stranded assets. *Stranded assets* are defined as the amount of initial holdings plus deposits minus withdrawals, in US dollars. *Initial holdings* represents the starting value of assets in the account. It is the baseline amount from which any changes in asset value due to transactions will be measured. Adding *deposits* to the initial holdings accounts for any additional funds or assets that were placed into the account after the initial holdings were established. Subtracting *withdrawals* from the sum of initial holdings and deposits reflects the reduction in asset value due to funds being taken out of the account. Thus, *stranded assets* captures the net value of assets that remain in the account after all transactions have occurred. These remaining assets are considered stranded because they are still in the account at the time of the bankruptcy and cannot be easily converted to cash or otherwise utilized. The *stranded asset ratio* is the amount of stranded assets in USD divided by stranded assets plus withdrawals. The *stranded asset indicator* equals 1 if the user has stranded assets ratio greater than 25%. In columns (1) and (2), the dependent variable is the stranded asset ratio, while columns (3) and (4) test the stranded asset indicator as the dependent variable. We include a series of user demographic indicator variables described in Section 4.1.1 as explanatory variables. Columns (2) and (4) include Earn Account token holdings as controls. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Stranded asset ratio		Stranded asset indicator	
	(1)	(2)	(3)	(4)
Male indicator	-0.030***	-0.008***	-0.110***	-0.031***
	(0.001)	(0.001)	(0.005)	(0.005)
Anglo-saxon indicator	0.007***	0.046***	0.043***	0.223***
	(0.002)	(0.002)	(0.009)	(0.009)
German indicator	0.010***	0.011***	0.038***	0.051***
	(0.002)	(0.002)	(0.010)	(0.010)
Hispanic indicator	0.007***	0.014***	0.030***	0.060***
	(0.002)	(0.002)	(0.011)	(0.011)
French indicator	-0.001	-0.003	-0.016	-0.027**
	(0.002)	(0.002)	(0.010)	(0.011)
Italian indicator	-0.018***	-0.028***	-0.095***	-0.145***
	(0.002)	(0.002)	(0.010)	(0.011)
Chinese indicator	-0.032***	-0.029***	-0.126***	-0.127***
	(0.003)	(0.002)	(0.011)	(0.011)
Indian indicator	0.016***	0.023***	0.067***	0.102***
	(0.002)	(0.002)	(0.012)	(0.012)
Russian indicator	-0.003	-0.009***	-0.025**	-0.055***
	(0.003)	(0.003)	(0.013)	(0.013)
Arabic indicator	0.013***	0.014***	0.042***	0.054***
	(0.003)	(0.003)	(0.014)	(0.015)
African indicator	0.026***	0.020***	0.120***	0.107***
	(0.003)	(0.003)	(0.017)	(0.018)
Controls	No	Yes	No	Yes
Observations	492,429	492,429	492,429	492,429
R-squared	0.003	0.115	0.003	0.079

Table A4: **Stranded Assets and Celsius Account and Token Use**

	Stranded asset ratio		Stranded asset indicator	
	(1)	(2)	(3)	(4)
Initial Earn account holdings (USD)	-0.045***	-0.045***	-0.224***	-0.226***
	(0.000)	(0.000)	(0.002)	(0.002)
Had Custody account	-0.372***	-0.380***	-1.078***	-1.127***
	(0.002)	(0.002)	(0.007)	(0.007)
Had Withheld account	-0.441***	-0.450***	-1.171***	-1.228***
	(0.006)	(0.006)	(0.018)	(0.018)
Number of tokens held	0.008***	0.007***	0.045***	0.043***
	(0.000)	(0.000)	(0.001)	(0.001)
Holds Bitcoin indicator	-0.017***	-0.014***	-0.183***	-0.176***
	(0.001)	(0.001)	(0.007)	(0.007)
Holds Ethereum indicator	0.013***	0.011***	0.081***	0.072***
	(0.001)	(0.001)	(0.006)	(0.006)
Holds Stablecoin indicator	-0.044***	-0.043***	-0.134***	-0.133***
	(0.001)	(0.001)	(0.006)	(0.006)
Holds other tokens indicator	-0.051***	-0.049***	-0.201***	-0.195***
	(0.001)	(0.001)	(0.007)	(0.007)
Interest from Earn account (USD)	0.043***	0.043***	0.211***	0.213***
	(0.001)	(0.001)	(0.003)	(0.003)
Controls	No	Yes	No	Yes
Observations	492,429	492,429	492,429	492,429
R-squared	0.233	0.237	0.336	0.349

Table A5: **Stranded Assets and Monitoring Incentives (Large Accounts)**

This table extends our analysis of the relation between monitoring incentives and stranded assets on the intensive and extensive margin by focusing solely on users with account holdings greater than above $1000 USD. The dependent variables in columns (1) through (2) are the stranded asset ratio, and in columns (3) through (4) are the stranded asset indicator. The independent variables include an institution indicator and the logarithm of 1 plus initial holdings. Columns (2) and (4) include additional controls for demographics and account use. Robust standard errors are reported in parentheses. For the probit regressions in Columns (3) and (4), the pseudo R-squared is reported. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Stranded asset ratio		Stranded asset indicator	
	(1)	(2)	(3)	(4)
Institution indicator	-0.086***	-0.083***	-0.502***	-0.506***
	(0.020)	(0.020)	(0.083)	(0.084)
Initial Earn account holdings (USD)	-0.026***	-0.022***	-0.159***	-0.138***
	(0.000)	(0.000)	(0.002)	(0.002)
Controls	No	Yes	No	Yes
Observations	299,493	299,493	299,493	299,493
R-squared	0.049	0.060	0.070	0.086

Table A6: **Cultural Sensitivity to Traditional Information Signals**

This table explores whether elements of cultural heritage can amplify or mediate the response to traditional informational signals before Celsius officially halted withdrawals. In all columns, the dependent variable is an indicator variable for withdrawal from the user's Earn account. All specifications include user-fixed effects, and robust standard errors clustered by user and week are reported in parentheses. Across the columns, we vary Hofstede's cultural elements. In columns (1) and (2), we focus on Individualism, the cultural element posited to amplify reactions, and in columns (3) and (4), we focus on Power Distance, the cultural element posited to mediate reactions. Even columns drop observations during the Terra Luna collapse, and odd columns include an indicator variable for the Terra Luna collapse time period. Additional explanatory variables, including market signals of price and volume, as well as their respective interaction terms, are included but not displayed for brevity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dep. var. = Withdrawal Indicator			
	Amplifying reaction Individualism (IDV)		Mediating reaction Power distance (PDI)	
	(1)	(2)	(3)	(4)
Celsius news sentiment	-0.034***	-0.034***	-0.039***	-0.040***
	(0.006)	(0.006)	(0.007)	(0.007)
CEL news sentiment × culture	-0.000	-0.001	0.001**	0.002**
	(0.000)	(0.000)	(0.001)	(0.001)
Insider withdrawal indicator	0.046***	0.046***	0.052***	0.052***
	(0.006)	(0.006)	(0.007)	(0.007)
CEL insider withdrawal × culture	0.001***	0.001***	-0.001***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.001)
Additional explanatory variables	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes
Terra Luna controls	Yes	No	Yes	No
Drop Terra Luna observations	No	Yes	No	Yes
Observations	5,909,148	5,416,719	5,909,148	5,416,719
R-squared	0.165	0.155	0.165	0.155

Table A7: **Stranded Assets and Uncertainty Avoidance**

This table examines the relation between Celsius depositor cultural heritage on the intensive and extensive margin. The dependent variables in columns (1) through (2) are the stranded asset ratio, and in columns (3) through (4) are the stranded asset indicator. While we include controls for all of Hofstede's six cultural elements in Columns (2) and (4), we focus on those that our theoretical framework posits as most important and uncertainty avoidance. For the probit regressions in Columns (3) through (4), the pseudo R-squared is reported. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Dep. var. =			
	Stranded asset ratio		Stranded asset indicator	
	(1)	(2)	(3)	(4)
Uncertainty avoidance (UAI)	0.003***	0.000	0.006***	-0.012
	(0.001)	(0.002)	(0.002)	(0.011)
Individualism (IDV)		-0.025***		-0.103***
		(0.004)		(0.018)
Power distance (PDI)		0.008***		0.020**
		(0.002)		(0.010)
Controls	No	Yes	No	Yes
Observations	492,429	492,429	492,429	492,429
R-squared	0.001	0.062	0.001	0.001

Table A8: **Stranded Assets and Trust**

This table examines the relation between Celsius depositor's trust and withdrawals on the intensive and extensive margin. The dependent variables in columns (1) through 32) are the stranded asset ratio, and in columns (4) through (6) are the stranded asset indicator. Controls include number of unique tokens held as well as initial balances of Bitcoin, Ethereum, stablecoins, alternative tokens, and demographics. Cultural heritage controls encompass all of Hofstede's six cultural elements, although we only report those that our theoretical framework identifies as most important, as well as uncertainty avoidance. For the probit regressions in Columns (3) through (4), the pseudo R-squared is reported. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Dep. var. =					
	Stranded asset ratio			Stranded asset indicator		
	(1)	(2)	(3)	(4)	(5)	(6)
Trust	-0.002***	0.000	0.012***	-0.001	0.002	0.051***
	(0.001)	(0.001)	(0.003)	(0.002)	(0.004)	(0.012)
Individualism (IDV)			-0.034***			-0.135***
			(0.004)			(0.020)
Power distance (PDI)			0.008***			0.020**
			(0.002)			(0.010)
Uncertainty avoidance (UAI)			0.004*			0.006
			(0.002)			(0.012)
Controls	No	Yes	Yes	No	Yes	Yes
Culture controls	No	No	Yes	No	No	Yes
Observations	492,429	492,429	492,429	492,429	492,429	492,429
R-squared	0.001	0.062	0.062	0.01	0.047	0.048

Table A9: **Traditional Information Signals and Uncertainty Avoidance**

This table explores another one of Hofstede's cultural elements: uncertainty avoidance. In columns (1) and (2), the dependent variable indicates whether a user withdrew from their Earn account, and in columns (3) and (4), it represents the user's normalized withdrawal amount from their Earn account. All specifications include user fixed effects, and robust standard errors clustered by user and week are reported in parentheses. Even columns drop observations during the Terra Luna collapse, and odd columns include an indicator variable for the Terra Luna collapse time period. Additional explanatory variables, including market signals of price and volume, as well as their respective interaction terms, are included but not displayed for brevity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dep. var. =			
	Withdrawal indicator		Withdrawal amount	
	Mediating reactions			
	Uncertainty avoidance (UAI)			
	(1)	(2)	(3)	(4)
Celsius news sentiment	-0.043***	-0.044***	-0.059***	-0.061***
	(0.007)	(0.007)	(0.009)	(0.010)
CEL news sentiment × culture	0.002***	0.003***	0.008***	0.008***
	(0.000)	(0.000)	(0.001)	(0.001)
Insider withdrawal indicator	0.061***	0.061***	0.053***	0.052***
	(0.008)	(0.008)	(0.010)	(0.010)
CEL insider withdrawal × culture	-0.004***	-0.004***	-0.007***	-0.007***
	(0.000)	(0.000)	(0.001)	(0.001)
Additional explanatory variables	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes
Terra Luna controls	Yes	No	Yes	No
Drop Terra Luna observations	No	Yes	No	Yes
Observations	5,909,148	5,416,719	5,909,148	5,416,719
R-squared	0.184	0.183	0.165	0.156

Table A10: **Comparison of Wallets Matched Via Crypto-Forensics Process**

This table examines the relation between wallets we were able to identify via the crypto-forensic process and those we could not identify (e.g., they had no transactions in ERC-20 tokens). We compare the matched and unmatched wallets for the Celsius users based on demographic and cultural characteristics and their initial holdings and interest earned. We report the mean for the wallets unmatched and matched in columns (1) and (2), respectively. The difference in means is reported in column (3), and the p-value associated with the test of differences in means is in column (4).

	Unmatched	Matched	Diff.	p-value
Panel A. Demographic characteristics	(1)	(2)	(3)	(4)
Male indicator	0.736	0.813	-0.078	0.000
Female indicator	0.201	0.132	0.068	0.000
Unknown gender	0.063	0.054	0.009	0.000
Anglo-Saxon indicator	0.261	0.304	-0.042	0.000
German indicator	0.127	0.114	0.013	0.000
Hispanic indicator	0.094	0.080	0.013	0.000
French indicator	0.095	0.101	-0.006	0.000
Italian indicator	0.093	0.084	0.008	0.000
Chinese indicator	0.067	0.090	-0.022	0.000
Indian indicator	0.065	0.053	0.011	0.000
Russian indicator	0.048	0.038	0.010	0.000
Arabic indicator	0.034	0.030	0.004	0.000
African indicator	0.023	0.016	0.008	0.000
Panel B. Cultural characteristics				
Power distance (PDI)	55.80	54.85	0.95	0.000
Individualism (IDV)	59.14	60.46	-1.32	0.000
Uncertainty avoidance (UAI)	62.28	60.54	1.74	0.000
Panel C. Celsius use				
Number of tokens held	3.2	5.8	-2.6	0.000
Holds BTC indicator	0.70	0.89	-0.19	0.000
Holds ETH indicator	0.38	1.00	-0.62	0.000
Holds Stablecoin indicator	0.26	0.46	-0.20	0.000
Holds Other tokens indicator	0.75	0.85	-0.10	0.000
Initial Earn account holdings (USD)	14,793	74,776	-59,982	0.000
Interest earned	149.87	498.78	-348.91	0.000
Stranded asset ratio	0.87	0.19	0.68	0.000
Observations	461,136	31,293	492,429	492,429

Table A11: **Comparison of Forensic-Matched Stranded Asset Holders**

This table examines the relation between wallets we were able to identify via the crypto-forensic process that had stranded assets and did not. We compare those with and without stranded assets from the selected subsample of matched wallets to better understand the differences among this group of Celsius users based on demographic and cultural characteristics, initial holdings, and interest earned. We report the mean for the wallets without stranded assets and with stranded assets in columns (1) and (2), respectively. The difference in means is reported in column (3), and the p-value associated with the test of differences in means is in column (4).

	No Stranded Assets	Stranded Assets	Diff.	p-value
Panel A. Demographic characteristics	(1)	(2)	(3)	(4)
Male indicator	0.804	0.840	-0.036	0.000
Female indicator	0.140	0.111	0.029	0.000
Unknown gender	0.056	0.048	0.007	0.008
Anglo-Saxon indicator	0.291	0.339	-0.047	0.000
German indicator	0.115	0.109	0.006	0.132
Hispanic indicator	0.075	0.094	-0.019	0.000
French indicator	0.104	0.090	0.015	0.000
Italian indicator	0.091	0.065	0.026	0.000
Chinese indicator	0.091	0.085	0.006	0.087
Indian indicator	0.053	0.054	-0.001	0.595
Russian indicator	0.041	0.033	0.008	0.001
Arabic indicator	0.032	0.024	0.008	0.001
African indicator	0.033	0.025	0.008	0.617
Panel B. Cultural characteristics				
Power distance (PDI)	55.16	53.93	1.23	0.000
Individualism (IDV)	60.36	60.77	-0.41	0.194
Uncertainty avoidance (UAI)	60.84	59.66	1.18	0.000
Panel C. Celsius use				
Number of tokens held	5.3	7.0	-1.7	0.000
Holds BTC indicator	0.89	0.92	-0.03	0.000
Holds ETH indicator	1.00	1.00	0.00	N.A.
Holds Stablecoin indicator	0.44	0.54	-0.11	0.000
Holds Other tokens indicator	0.82	0.90	-0.08	0.000
Initial Earn account holdings (USD)	71,263	84,825	-13,562	0.138
Interest earned	400.33	780.44	-380.10	0.000
Stranded asset ratio	0.03	0.66	-0.64	0.000
Observations	23,188	8,105	31,293	31,293

Table A12: **Cultural Sensitivity to the Collapse Itself**

This table further explores whether elements of cultural heritage can alter trading volume in the presence of stranded assets after withdrawals were halted at Celsius. In this specification, we relax the assumption that it was primarily wallets with stranded assets that had a differentiated cultural response, allowing all wallets to the collapse. In all Panels, the dependent variables are the total number of transactions, categorized as either send or receive transactions to remove smart contract and bot activity (columns 1-2), transactions in low-risk tokens (columns 3-4), transactions in high-risk tokens (columns 5-6). We employ the triple-differences specification from Eq. (3). In Panel A, the focal variable is the single-difference interaction, which includes an indicator for low culture (Q1) interacting with *Post*. In Panel B, the focal variable is an indicator for high culture (Q4) interacted with *Post*. Quartiles are computed from the sample distribution of the depositor-level cultural index, which is mapped from Hofstede's measures. All regressions use ordinary least squares with wallet and week fixed effects. Robust standard errors, clustered by wallet, are reported in parentheses. For brevity, additional explanatory variables are omitted from the table. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dep. var. =					
	Send/receive transactions		Low risk tokens		High risk tokens	
	Individualism	Power distance	Individualism	Power distance	Individualism	Power distance
	(IDV)	(PDI)	(IDV)	(PDI)	(IDV)	(PDI)
Panel A. Low culture	(1)	(2)	(3)	(4)	(5)	(6)
1{Culture $\leq Q1$}× Post	0.002	-0.020***	-0.002	-0.006***	0.001	-0.001**
	(0.008)	(0.007)	(0.002)	(0.002)	(0.000)	(0.000)
Panel B. High culture						
1{Culture $\geq Q4$}× Post	-0.030***	0.000	-0.009***	-0.001	-0.000	0.001**
	(0.008)	(0.007)	(0.002)	(0.002)	(0.000)	(0.000)
Terra Luna controls	Yes	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	625,166	625,166	625,166	625,166	625,166	625,166
R-squared	0.185	0.185	0.152	0.152	0.087	0.087

Table A13: **Wallet Transactions and Uncertainty Avoidance**

This table further examines the extent to which cultural heritage alters trading after withdrawals were halted at Celsius. In this specification, we relax the assumption that it was primarily wallets with stranded assets that had a differentiated cultural response, allowing all wallets to respond. In all Panels, the dependent variables are the total number of transactions, categorized as either send or receive transactions to remove smart contract and bot activity (columns 1), transactions in low-risk tokens (columns 2), transactions in high-risk tokens (columns 3). We use the triple-differences specification from Eq. (3). In Panel A, the focal variable is the triple interaction, which uses an indicator for low culture (Q1) interacted with $Post \times Treat$. In Panel B, the focal variable is an indicator for high culture (Q4) interacted with $Post \times Treat$. Quartiles are computed from the sample distribution of the depositor-level cultural index, which is mapped from Hofstede's measures. All regressions use ordinary least squares with wallet and week fixed effects. Robust standard errors, clustered by wallet, are reported in parentheses. For brevity, additional explanatory variables are omitted from the table. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dep. var. =		
	Send/receive transactions	Low-risk tokens	High-risk tokens
Panel A. Low culture	(1)	(2)	(3)
1{Uncertainty Avoidance $\leq Q1$}× Post × Treat	-0.025*	-0.005	0.000
	(0.013)	(0.014)	(0.000)
Panel B. High culture			
1{Uncertainty Avoidance $\geq Q4$}× Post × Treat	0.032**	0.006*	-0.001
	(0.014)	(0.004)	(0.001)
Terra Luna controls	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes
Observations	625,166	625,166	625,166
R-squared	0.185	0.185	0.087

Appendix A. Online Appendix A.

1. Accounts
   (a) **Custody**: Coins could be transferred, swapped, or used as collateral for loans, but did not earn rewards.
   (b) **Earn**: Coins earned interest but could not be swapped or pledged as collateral. Assets in Earn accounts could only be transferred back to Custody.
   (c) **Withhold**: Accounts designated for unaccredited investors in nine U.S. states where Celsius lacked licenses to offer Custody.[8]
2. Transaction Types
   (a) **Deposit**: Bringing in new assets from outside the platform.
   (b) **Transfer**: Moving coins between Custody and Earn accounts.
   (c) **Swap**: Exchanging one cryptocurrency for another (e.g., ETH for BTC).
   (d) **Interest/Rewards**: Earnings on coins in Earn accounts, paid in-kind or in CEL tokens.
   (e) **Collateral**: Assets pledged to secure loans.
   (f) **Loan Payments**: Principal and interest repayments.
   (g) **Liquidations**: Loan principal or interest satisfied through collateral sales.
   (h) **Withdrawal**: Removing funds from the platform.
   (i) **Operational Costs**: Miscellaneous fees and platform-level adjustments.

[8]The nine states were: Connecticut, Louisiana, Nebraska, Nevada, New York, North Carolina, Ohio, Vermont, and Washington.

Appendix B. Online Appendix B.

B.1. A Model of Withdrawals with Cultural Influence

This model is an extension of the canonical global-games framework for runs of Morris and Shin (1998). Let there be a unit mass of digital depositors $i \in [0,1]$, each with balance $B_i > 0$. The digital platform's fundamentals $\theta \in \mathbb{R}$ (higher is better) is drawn once from a continuous prior with density $f(\theta)$. θ is a latent variable capturing the economic health of the digital platform. Formally, θ drives the platform's true solvency capacity:

If θ is high, the platform's asset values or liquidity are strong enough to honor withdrawals.

If θ is low, the platform is fragile, and even modest withdrawals can tip it into failure.

In this model, we abstract from placing an exact unit on θ, but one can think of it as an underlying solvency index or as reflecting the quality and liquidity of token reserves more generally. At present, θ simply summarizes the platform's true financial health. For modeling purposes, what is important is that depositors do not observe θ directly. Instead, they receive noisy private signals. If the platform fails by the terminal date, a fraction $L \in (0,1]$ of any funds left inside is lost. If the platform survives, remaining funds earn gross return $1 + r$.

The key innovation in our extension is that while θ captures objective fundamentals, depositors' responses to signals about θ are systematically shaped by cultural dimensions such as individualism and power distance, which shift withdrawal thresholds without altering underlying solvency. Specifically, let each depositor choose two things. First, whether to initiate a withdrawal $D_i \in \{0,1\}$. This represents the extensive margin. Second, if $D_i = 1$, the depositor also must choose a withdrawal share $y_i \in [0,1]$. This represents the intensive margin. Let the aggregate withdrawal share be $\bar{y} \equiv \int_0^1 y_j \, dj$. The platform fails with probability $\Pr(\text{Fail} \mid \theta, \bar{y}) = \pi(\theta, \bar{y})$, where $\pi_\theta(\cdot) < 0$ and $\pi_{\bar{y}}(\cdot) > 0$.

Each depositor observes a private signal $x_i = \theta + \varepsilon_i$, with $\varepsilon_i \sim \mathcal{N}(0, \sigma_x^2)$, and a public authority message $m = \theta + \nu$, with $\nu \sim \mathcal{N}(0, \sigma_m^2)$. You can think of the public authority message as positive news sentiment stemming from an interview with Celsius' CEO. When the depositor initiates a withdrawal, she incurs a cost. Initiating a withdrawal has a fixed cost $k_0 \geq 0$, and there are variable costs which increase with the size of the withdrawal $k(y) = k_1 y + \frac{1}{2} k_2 y^2$, with $k_1, k_2 > 0$.

The fixed component k_0 follows the standard approach in Morris and Shin (1998), where a small participation cost ensures that investors withdraw only when fundamentals are sufficiently weak. In the context of digital platforms, k_0 can be interpreted as the gas fee, the attention cost of monitoring solvency, or the friction of losing the high interest available in the Earn account. This cost creates a meaningful extensive

margin. Without it, even a marginally negative signal would induce every depositor to withdraw a fraction of their balance. The variable components $k_1 y$ and $\frac{1}{2}k_2 y^2$ capture the fact that larger withdrawals are progressively more costly. Together, these costs inform both the decision of whether to withdraw at all and the choice of how much to withdraw, which aligns with our focus on individuals with stranded assets and their corresponding stranded asset ratios.

Next, we add our cultural elements to the model by embedding two of Hofstede's dimensions of societal culture as preference shifters. First, consider individualism (IDV), let $\iota_i \in [0, 1]$ denote investor i's individualism index. A lower ι_i (more collectivist) implies a higher cost of deviating from peers' actions. We model a disutility from deviating from peers' average withdrawal:

$$\alpha(\iota_i)\tfrac{\phi}{2}\big(y_i - \bar{y}\big)^2,$$

with $\phi > 0$ and $\alpha'(\cdot) < 0$. Thus, more individualistic investors face a smaller conformity penalty.

Second, consider Power Distance (PDI), let $p_i \in [0, 1]$ be investor i's power-distance index. We allow PDI to operate through belief formation and authority alignment. We will provide intuition for these two channels before showing the mathematical notation. Namely, the first channel is the belief channel, where depositors with higher PDI put greater weight on official reassurances when forming expectations about fundamentals. Even if the message m is noisy, they effectively treat it as more precise, thereby perceiving lower failure risk than an otherwise identical low-PDI depositor.

The second channel is the alignment channel, where high-PDI depositors also derive utility from following authority guidance itself, independent of its informational content. When the authority recommends "hold," deviating from this guidance imposes a direct penalty. Both channels push in the same direction under reassurance. High-PDI depositors withdraw later and less aggressively. In contrast, low-PDI depositors treat the public message with the weight implied by its statistical precision and feel little direct penalty from ignoring official guidance. Mathematically, these channels are defined as follows:

PDI belief channel:

$$\tau_m(p_i) \equiv \sigma_m^{-2}(1 + \kappa p_i), \qquad \kappa \geq 0,$$

so higher p_i overweights the message relative to Bayesian precision. Let $\tau_x \equiv \sigma_x^{-2}$. Investor i's posterior mean is

$$\mu_i = \omega_x x_i + \omega_m(p_i)m, \quad \omega_x = \frac{\tau_x}{\tau_x + \tau_m(p_i)}, \quad \omega_m(p_i) = \frac{\tau_m(p_i)}{\tau_x + \tau_m(p_i)}.$$

PDI alignment channel: Suppose the authority recommends an action $a \in \{\text{hold}, \text{withdraw}\}$. Misalignment yields a penalty $\delta(p_i)\gamma \cdot |y_i - \mathbb{1}\{a = \text{withdraw}\}|$, with $\delta'(p) > 0$ and $\gamma > 0$. We assume $a = \text{hold}$ as the Celsius CEO would always be incentivized to tell the users to hold their deposits with him.

Next, we calculate the expected payoff for the depositor based on her decision. Given μ_i and the conjectured $\bar{y}$, the expected monetary loss per dollar left is $\ell(\mu_i, \bar{y}) \equiv L \cdot \pi(\mu_i, \bar{y})$. Depositor i's expected utility $U_i(y_i; \mu_i, \bar{y}, a)$ from withdrawal choice y_i is expressed as follows:

$$= -(1 - y_i)B_i\,\ell(\mu_i, \bar{y}) - \left(k_0 \cdot \mathbb{1}\{y_i > 0\} + k_1 y_i + \tfrac{1}{2}k_2 y_i^2\right) - \alpha(\iota_i)\tfrac{\phi}{2}(y_i - \bar{y})^2 - \delta(p_i)\gamma \cdot |y_i - \mathbb{1}\{a = \text{withdraw}\}|$$

The expression shows that the expected payoff to the depositor balances two opposing forces. On the one hand, withdrawing reduces exposure to potential losses if the platform fails (i.e., the first term $(1 - y_i)B_i\,\ell(\mu_i, \bar{y})$). On the other hand, withdrawing is costly along three dimensions (i.e., the next three terms). First, there are fixed and variable frictions. Then, there are the social and authority penalties. Given this expected utility, we know that the depositor will only withdraw if the expected benefits of withdrawing outweigh the costs. Next, we use this expression to show exactly how this trade-off determines both the decision of whether to withdraw at all and the amount to withdraw if they do.

On the extensive margin, the depositor will withdraw if and only if the value of a small withdrawal exceeds k_0. The net marginal gain from initiating a withdrawal is expressed as follows:

$$\Delta_i^{\text{ext}}(\mu_i, \bar{y}, a) \equiv B_i\,\ell(\mu_i, \bar{y}) - k_1 - \alpha(\iota_i)\phi \cdot |0 - \bar{y}| - \delta(p_i)\gamma \cdot \mathbb{1}\{a = \text{hold}\}$$

Because $\ell(\mu_i, \bar{y})$ decreases in μ_i, there exists a cutoff $s^*(\bar{y}; \iota_i, p_i, a)$ such that investor i initiates if and only if $x_i \leq s^*$. This follows from the expression of the posterior mean ($\mu_i = \omega_x x_i + \omega_m(p_i)m$). It tells us that if x_i is lower (i.e., a worse signal about solvency), then μ_i is lower, so expected loss ($\ell(\mu_i, \bar{y})$) is higher. Thus, as x_i falls, the net marginal gain increases monotonically. Similarly, we see that the cutoff is increasing in ι_i (i.e., more individualistic depositors withdraw earlier) and decreasing in p_i (i.e., higher-PDI depositors wait longer when $a = \text{hold}$).

Turning to the intensive margin, we need to set the first-order condition (FOC) equal to zero in order to derive the optimal withdrawal share y_i^*. The FOC is:

$$\frac{\partial U_i}{\partial y_i} = B_i\,\ell(\mu_i, \bar{y}) - k_1 - k_2 y_i - \alpha(\iota_i)\phi(y_i - \bar{y}) - \delta(p_i)\gamma = 0.$$

Thus, rearranging gives:

$$y_i^*(\mu_i, \bar{y}; \iota_i, p_i) = \frac{B_i\, \ell(\mu_i, \bar{y}) - k_1 - \delta(p_i)\gamma + \alpha(\iota_i)\phi\, \bar{y}}{k_2 + \alpha(\iota_i)\phi},$$

.

We see that $B_i\, \ell(\mu_i, \bar{y})$ is the fundamental driver, which makes sense. The larger the balance and the higher the expected loss, the stronger the incentive for the depositor to withdraw. This is offset by the marginal cost of withdrawing (k_i), the authority alignment penalty, and the collectivism pull toward the group average. The denominator acts like resistance to big swings, with higher collectivism or variable costs flattening out the response.

Turning to the comparative statistics for the societal cultural elements of interest. $\partial y_i^*/\partial \iota_i \geq 0$ tells us that more individualism raises withdrawal share and $\partial y_i^*/\partial p_i \leq 0$ tells us that higher power distance lowers withdrawal share when a = hold. Ultimately, individualism increases withdrawal intensity, reducing the stranded asset ratio for those who do end up stranded. Whereas, high-PDI depositors may believe in the fundamentals (belief channel) and also feel a cost or penalty from defying authority (alignment channel). Both lower their actual withdrawal share. On the intensive margin, individualism sharpens and deepens responses, whereas power distance dampens them. This helps explain why the two cultural dimensions generate opposite predictions. This leads to two of our testable hypotheses.

> *Proposition 1: Extensive margin.* Suppose the authority figure, like CEO Mashinsky, recommends hold. Then, holding fundamentals and balances fixed, higher individualism raises the initiation cutoff, reducing the probability of becoming a person with stranded assets. Higher power distance lowers the initiation cutoff, increasing the probability of becoming a person with stranded assets.
>
> *Proposition 2: Intensive margin.* Conditional on initiating, the optimal withdrawal share satisfies the expression above. Higher individualism increases the withdrawal share, thereby lowering the stranded asset ratio. Higher power distance reduces the withdrawal share, thereby raising the stranded asset ratio.

3. Online Appendix C.

In this section, we describe our additional tables and figures in more detail. To gain a deeper understanding of user behavior and the flow of assets within the Celsius platform during our timeframe, we compare withdrawals and deposits across different tokens. Figure A1 provides a detailed analysis of Earn Account withdrawals and deposits by token from April 14 to June 12, 2022.

[Insert Figure A1 here]

The figure illustrates notable fluctuations in both deposits and withdrawals throughout this period. Panel A displays the withdrawal values in U.S. dollars for Bitcoin, Ethereum, stablecoins, and other tokens. The data reveals significant spikes, particularly in mid-May 2022 when Terra Luna collapsed. During this period, we see that all tokens experienced a sharp surge in withdrawals, with stablecoins tokens peaking at nearly $175 million USD. Following this peak, withdrawal activity generally declined but showed a resurgence in early June, especially for Bitcoin and Ethereum.

Panel B shows the deposit activity, which also peaked around mid-May 2022, though at a lower scale compared to withdrawals, with the highest deposit value slightly exceeding $30 million USD. Notably, Bitcoin and Ethereum deposits increased during the same periods of heightened withdrawal activity. Panel B also demonstrates more frequent fluctuations in deposits, suggesting periods of increased market volatility or trading activities that influenced deposit patterns more dynamically compared to withdrawals.

Table A1 provides a detailed breakdown of the geographic distribution of institutions, highlighting the concentration of entities across different countries. We list the top 12 countries and group the remaining 40 countries into a separate category.

[Insert Table A1 here]

The majority of institutions are located in the US, which accounts for 1,174 entities, representing 58.8% of the total. Following the U.S., Australia emerges as the second most significant location, with 491 entities comprising 24.6% of the total. Canada and the United Kingdom also show notable representations, with 5.0% (99 entities) and 2.0% (40 entities), respectively. Smaller yet still significant concentrations are found in Hong Kong (1.2%), the Cayman Islands (1.1%), and the Virgin Islands (British) (0.9%), which are known for their roles in regional financial services and offshore banking.

A total of 40 other countries collectively account for 4.00% of the entities, indicating a wide but less concentrated distribution across the rest of the world. The presence of entities in diverse locations such as Singapore (0.80%), South Africa (0.55%), and New Zealand (0.30%) suggests a global distribution of institutions transacting on the Celsius Network.

Table A2 provides a summary of the number of transactions and the total transaction value (in USD millions) for various cryptocurrencies on the Celsius platform. The table lists specific tokens along with a category for 40 other tokens.

[Insert Table A2 here]

Bitcoin leads with the highest number of transactions, totaling 771,281, and a transaction value of $4,817.91 million. Ethereum (ETH) follows with 465,142 transactions and a total value of $4,199.02 million. USDC, a stablecoin, also shows significant activity with 423,846 transactions and a transaction value of $3,307.29 million. CEL, the native token of the Celsius platform, has 295,180 transactions with a total value of $257.50 million. In the lower range, tokens such as BNB and AAVE have fewer transactions (25,237 and 24,719, respectively) with lower transaction values ($35.79 million for BNB and $16.00 million for AAVE). The category for 40 other tokens aggregates 270,652 transactions with a total value of $739.02 million. Overall, the table highlights the dominance of Bitcoin, Ethereum, and stablecoins like USDC in both transaction volume and value on the Celsius platform, while other tokens like CEL, MATIC, and ADA also show significant activity. The diversity in transaction values across tokens indicates varying levels of usage and market importance for each cryptocurrency.

Table A3 provides insights into the relation between demographic characteristics and the extent of stranded assets in Celsius accounts at the time of bankruptcy. Stranded assets are defined as the residual account value after all deposits and withdrawals have occurred, measured either as a ratio of initial holdings (columns (1)–(2)) or as an indicator for whether the user holds any stranded assets (columns (3)–(4)). Explanatory variables consist of demographic group indicators. Earn Account token holdings are included as controls in even-numbered columns.

[Insert Table A3 here]

The results reveal sharp demographic heterogeneity. Relative to the omitted categories, Anglo-Saxon, German, Hispanic, Indian, Russian, Arabic, and African users are significantly more likely to hold stranded assets. These correlations are both statistically and economically meaningful. For example, the German indicator is associated with an increase in the stranded asset ratio of roughly 1 percentage point (columns (1)–(2)), and with a 4-5 p.p. higher likelihood of any stranded assets (columns (3)–(4)). By contrast, the French indicator loads negatively, suggesting lower propensity

to retain stranded assets. The male indicator is negative and significant in the ratio specification but small in terms of economic magnitude.

Next, we examine the relation between account characteristics, such as token holdings and stranded assets, at the time of Celsius' account freezing. Table A4 shows that larger initial Earn account balances have a strong negative correlation with stranded asset ratios and a reduced likelihood of stranded holdings, consistent with large depositors monitoring more. When examining the types of tokens held, we find that the number of unique tokens has a positive and significant correlation with stranded assets, although the economic magnitude is small. Examining different types of tokens does not reveal a clear pattern. For example, holding Bitcoin has a negative and significant correlation in all specifications with a seemingly large economic magnitude. In contrast, holding Ethereum, another market-cap dominant token, has a positive and significant correlation in all specifications. Finally, somewhat surprisingly, accruing more interest from Earn accounts does not seem to be associated with monitoring, as this explanatory variable is positively correlated with stranded assets.

[Insert Table A4 here]

Table A5 presents the results of the regression analysis examining the relation between monitoring incentives and stranded asset user behavior, specifically excluding small accounts. The table is divided into four columns, each representing different regression models. The dependent variable in columns (1) and (2) is the *stranded asset ratio* for accounts with initial holdings greater than $1,000 USD, separately. The dependent variable in columns (3) and (4) is the *stranded asset indicator* for accounts with initial holdings greater than $1,000 USD, separately. In all specifications, being an institution or having higher initial holding is associated with lower stranded assets on both the intensive and extensive margin. Thus, the results indicate the importance of monitoring incentives in mitigating the presence of stranded assets for Celsius users, particularly among accounts with larger initial holdings.

[Insert Table A5 here]

Table A6 confirms that our cultural sensitivity results in relation to traditional information signals lead to similar statistical inferences when using a withdrawal indicator rather than withdrawal amounts. Table A7 and Table A9 extend our analysis of Hofstede's cultural dimensions to uncertainty avoidance (UAI). While our main focus is on individualism and power distance, UAI plausibly influences withdrawal behavior through a similar channel to power distance. Users from high-UAI cultures perceive a higher cost of acting under ambiguity, delaying withdrawal until signals become unambiguous. Consistent with this hypothesis, we find that high-UAI users behave like high power-distance users on both the intensive and extensive margins, though the effects are somewhat smaller. Moreover, UAI significantly mediates how users respond to traditional information signals.

[Insert Table A6 here]

[Insert Table A7 here]

[Insert Table A9 here]

Next, Figure A2 plots weekly transaction patterns in the ten weeks before and after the Celsius halt of withdrawals for our subsample of wallets associated with names listed in the Celsius bankruptcy filings. While the plot demonstrates that the two groups (those with and without stranded assets) followed relatively similar patterns, it is also clear that the Terra-Luna collapse, which first showed signs of a run on May 7, 2022 (5 weeks before Celsius halt) led to a dramatic increase in transaction volume. Therefore, we also assess how similar the groups were on a number of demographic, cultural, and Celsius account dimensions.

[Insert Figure A2 here]

In Table A10 and Table A11, we compare wallets identified via the crypto-forensics process to those that could not be matched, and then examine differences between matched wallets with and without stranded assets. Matched wallets are more likely to be male, Anglo-Saxon, and from cultures with higher individualism and lower uncertainty avoidance. Matched wallets also hold more tokens, are more likely to include Bitcoin and Ethereum, and have larger balances and accrued interest. Within the matched sample, stranded asset holders are similarly male and Anglo-Saxon, with somewhat lower power-distance and higher Individualism scores. They hold more tokens, are more likely to hold stablecoins, and exhibit higher balances and accrued interest. Taken together, these results indicate that the forensic matching process identifies a non-random subset of users and that stranded assets were disproportionately concentrated among those with more complex, non-stablecoin portfolios.

[Insert Table A10 here]

[Insert Table A11 here]

In Table A12, we relax the assumption that culture operates only through stranded assets and allow for broader post-collapse reactions. Results show that both individualism and power distance shape adjustment behavior, with six of twelve specifications significant, including for high-risk tokens. Table A13 extends the analysis to uncertainty avoidance, where high-UAI users—who were more likely to be stranded pre-freeze—also display distinct post-collapse repair, shifting transactions toward safer tokens. Together, the evidence indicates that cultural sensitivity influences portfolio adjustment both through the collapse itself and through subsequent responses among stranded asset holders.

[Insert Table A12 here]

[Insert Table A13 here]