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

Abstract

Celsius was not a bank, but the now-bankrupt cryptocurrency network advertised and provided de facto banking services. We investigate the consequences of this collapse for Celsius's depositors. First, we summarize deposits by demographic and institutional affiliation. Then, we examine the intensive and extensive margin differences in digital assets stranded in bankruptcy. We find significant disparities across demographic groups, with institutions, males, and ethnic groups culturally distant from Celsius's founders doing better. Mechanism tests are consistent with more effective monitoring of risk by these groups. Finally, using a difference-in-differences approach, we analyze the influence of stranded assets on user's subsequent digital asset balances and transactions. We find significant differences in behavior, with those most impacted by the bankruptcy moving away from DeFi and NFTs toward more basic transactions (e.g., buy and hold) but also exhibiting tendencies to gamble for resurrection by holding riskier cryptocurrencies (e.g., meme coins). We conclude with a discussion of the implications for policymakers and industry participants, aiming to enhance the stability and resilience of digital asset markets.

Keywords: cryptocurrency, blockchain, tokens, digital assets, decentralized finance, DeFi, FinTech, lending, banking, financial intermediation, bankruptcy, diversity, DEI, financial inclusion

JEL codes: *G32, G24, G28*

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1. Introduction

Bank runs are a persistent vulnerability in financial systems that have long been a subject of financial and economic research (Diamond and Dybvig, 1983; Goldstein and Pauzner, 2005; Iyer and Puri, 2012). The collapse of Celsius Network, a digital asset lending platform that marketed itself as a bank-like entity, presents a unique opportunity to examine a "bank-run"-like event in a decentralized context with limited regulation. Does the global accessibility and pseudonymous nature of decentralized digital asset platforms exacerbate information asymmetry and moral hazard problems? Can certain users overcome these market imperfections, and if so, who and why? Through empirical analyses of the collapse of the Celsius Network, we provide insight into these theoretical considerations and their practical implications for policymakers. More broadly, our study contributes to understanding the behavior and inclusivity of digital asset users (Kogan et al., 2024; Aiello et al., 2024a; Higgins, 2024) and the role of information, monitoring, and non-technological trust within these novel capital markets (Liu et al., 2023; Mishra et al., 2022).

Unlike traditional financial institutions, where depositor actions are private information, the Celsius Network collapse occurred on a blockchain, providing an immutable record of transactions and timelines. These unique properties of blockchains enable us to analyze the collapse of the Celsius Network in a very detailed way. Specifically, we gather transactions and wallet-holding data for the time period before and after the bankruptcy for all users of the Celsius Network between April 14, 2022, and June 12, 2022, when withdrawals were halted. While most blockchain data is pseudonymous in nature, the Celsius Network's downfall was unique because the names of depositors and balances were listed in the bankruptcy filings. Thus, we can merge immutable blockchain data with demographic information derived from the names in the bankruptcy filings, which we process to identify gender and ethnicity using leading algorithms. This approach allows us to explore the relationship between the decentralized deposit run and its consequences for various user groups and to describe the demographic characteristics, financial outcomes, and behavioral changes for those affected

by the Celsius Network's collapse.

We begin by examining the demographic composition of the Celsius Network's depositor base. A count of the user base reveals that most depositors are individuals, with institutions comprising only a tiny fraction of the total number of users. The depositor base is predominantly male with considerable ethnic diversity. Anglo-Saxon, German, and Hispanic individuals are the most represented groups.

Next, we analyze the characteristics of Earn Accounts on the Celsius Network, focusing on token holdings, transaction behaviors, and account balances. We observe that most accounts hold a small number of tokens, with Bitcoin (BTC) being the most commonly held cryptocurrency. Transaction activity varies, with a minority of accounts engaging in incoming and outgoing transactions. The interest earned on these accounts is generally low, and initial holdings show significant variation, with many accounts starting with relatively small amounts.

We also investigate the transaction flows within Earn Accounts, where we observe significant volatility, particularly around mid-May 2022. During this period, withdrawals spike dramatically, surpassing deposits by a wide margin. This trend suggests a heightened user response to concerns about Celsius, leading to substantial fluctuations in the flow of assets within the network.

Next, we examine the distribution of initial holdings in the Earn Accounts, which shows that a large majority of accounts have relatively low initial holdings, typically less than \$10,000. However, there is also a noticeable minority of accounts with much larger holdings, though these are significantly fewer in number. This distribution highlights the variation in user investment levels within the network.

Our analysis then turns to factors that explain the intensive and extensive margins of stranded assets. We define stranded assets as the net value of assets remaining in an account after all transactions, calculated as the initial holdings plus deposits minus withdrawals. These assets are considered stranded because they remain in the account at the time of

bankruptcy and cannot be easily liquidated. The stranded asset ratio measures the proportion of these assets relative to the total of stranded assets plus withdrawals (i.e., the intensive margin), while the stranded asset indicator is an indicator variable indicating whether an account has any stranded assets (i.e., the extensive margin).

We then explore the relation between stranded assets and depositor demographics. The analysis reveals significant disparities across different demographic groups, with males and certain ethnic groups (e.g., German, French, Italian, Chinese, and African) showing varying likelihoods of being associated with stranded assets. Individuals of Hispanic, Indian, Russian, and Arabic descent are more likely to have stranded assets and larger amounts of assets tied up.

Additionally, we investigate the role of monitoring incentives, particularly the involvement of institutional investors, in relation to stranded assets. The results indicate that institutional presence significantly reduces both the stranded asset ratio and the likelihood of having stranded assets. This suggests that institutional investors are more effective in mitigating the risk of stranded assets, likely due to better monitoring capabilities.

We also analyze the effect of stranded assets on wallet transactions, finding that users with stranded assets tend to increase the number of transactions after withdrawals are halted. Specifically, there is a notable increase in send and receive transactions, while the relation with other transaction types, such as DeFi or NFTs, is minimal or non-existent. These results indicate a shift in user behavior towards more basic transaction types in response to the restriction on withdrawals.

We then look at token transfer activity and find that users with stranded assets are more likely to send Ethereum (ETH) tokens but less likely to receive them after withdrawals were limited. For ERC-20 tokens, both sending and receiving activity increases under the same conditions. This suggests that the restriction on withdrawals has a differentiated impact on the transfer of different types of tokens.

Finally, we explore the impact of stranded assets on the receipt of tokens categorized

by risk level. The analysis shows that users with stranded assets are more likely to receive high-risk tokens after the withdrawal restrictions were imposed. In contrast, their use of stablecoins and low-risk tokens remains largely unchanged. This suggests a shift towards higher-risk assets among users with stranded assets.

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We conclude with a discussion of the policy implications. Given that we show retail investors and specific demographic groups, such as women, were disproportionately affected by Celsius Network's collapse, it is important to recognize the inadequacy of current regulatory frameworks. To address these vulnerabilities, we propose several policy directions: (i) refining the definition and regulatory requirements for decentralized banking entities, including enhanced risk disclosure, capital adequacy standards, and stress testing; (ii) exploring the feasibility and implementation of deposit insurance schemes for digital assets; and (iii) mandating user education and financial literacy requirements for participation in complex digital asset products. These proposals aim to balance innovation in DeFi with necessary consumer protections, potentially through experimental policy approaches to assess their efficacy in the unique context of digital asset markets.

Our paper contributes to the growing DeFi literature (Yermack, 2017; Harvey 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), to stablecoins (Catalini et al., 2022; Whited et al., 2023; Niepelt, 2024) and beyond. The closest vein of this research explores the demographic data of digital asset users (Auer et al., 2023; Aiello et al., 2024a,b; Kogan et al., 2024). We complement their work by shedding light on the demographics and behavior of digital 'bank' users. Further, we explore which digital 'bank' depositors are susceptible to cheap talk and, thereby, have stranded assets and

if their behavioral responses differ from other digital asset users.

Second, our work extends 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, by examining mechanisms of trust and cultural distance (Pan et al., 2017, 2019) developed in anthropology Hofstede (1991), we establish that even in technically "trustless" settings, users rely on cultural signals 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) have a pronounced influence on financial development and economic growth.

Third, we contribute to research on regulating digital assets and policy responses to digital "bank" runs. A related study explores the downfall of the stablecoin TerraLuna and its consequences. While there are similarities, the mechanisms we explore are more closely related to the traditional literature on banking and bank runs. These findings have policy implications and relate to a growing literature focusing on digital asset regulation (Guseva, 2021; Grennan, 2024).

Finally, we contribute to the literature on financial inclusion and how financial technology and decentralized digital assets and services help us achieve broader development goals (Higgins, 2024; Gertler et al., 2022). By providing empirical insights into the global spread of digital asset users, we contribute unique data, which is critical as measurement is key to understanding financial inclusion and identifying opportunities to expand it (Karlan et al., 2016; Demirgüç-Kunt et al., 2020).

2. Institutional Background

2.1. Hypotheses Development

A primary consequence of bank runs is the potential loss of depositor funds. Diamond and Dybvig (1983) present a model of bank runs, where depositors withdraw their funds due to panic, leading to a self-fulfilling prophecy of bank failure. A series of models have explored this key coordination challenge among depositors that stems from depositors' expectations concerning the behavior of other depositors (Rochet and Vives, 2004; Goldstein and Pauzner, 2005). Formal arrangements such as deposit insurance are tools for mitigating the consequences of bank runs and bankruptcy for consumers Diamond and Dybvig (1986); Iyer et al. (2016); Martin et al. (2023), yet digital 'banks' do not have deposit insurance. Informal arrangements stemming from trust, social networks, and/or high-quality bank-depositor relationships can also mitigate the influence of bank runs and risk (Iyer and Puri, 2012; Koudijs et al., 2021). Since decentralized, digital 'banks' are known for pseudonymous transactions and privacy, this may make traditional forms of trust and social connectedness moot or lead to coarser signals of trust based on publicly or strategically disclosed information (e.g., the experience of the founder and core developer teams).

The traditional bank run literature has also shown how bank runs can also lead to contagion effects, where the failure of one bank induces runs on other banks, causing a domino effect in the financial system and leading to widespread financial instability and economic downturns (Allen and Gale, 2000; Freixas et al., 2000). Yet we know relatively little about runs on digital assets and what happens to depositors with stranded assets. While there may be similarities between the traditional and digital realm, it is wrong to assume that the insights from traditional bank runs will hold in a digital context. Speed, scale, anonymity, and contagion risk differ in the digital context. Specifically, runs on digital assets can occur at a much faster pace due to the global nature of digital asset markets and the ease of transferring assets between platforms. Traditional bank runs are typically limited by geographical con-

straints, physical access to branches, and slower transfer mechanisms. Second, digital asset platforms often operate with a higher degree of anonymity and decentralization compared to traditional banks. This lack of a centralized authority may make it impossible to rely on informal mechanisms to update beliefs about reputation, which may lead to a complete unraveling through a classic lemons model (Akerlof, 1970). Third, while traditional bank runs can lead to systemic risks within the banking sector, runs on digital assets can spread across a wider range of interconnected platforms and assets or change digital asset users' behavior in unexpected ways.

Therefore, we explore several key questions about digital bank depositors, including: (i) who are the depositors in terms of demographic and institutional affiliation? (ii) what happens to digital depositors leading up to their assets becoming stranded in bankruptcy? (iii) why do some digital depositors appear to fare better? and (iv) what are the consequences of being more or less exposed to stranded assets from the digital bank failure?

2.2. Business Model of Celsius Network

Celsius Network operated as a crypto retail bank, offering high-interest savings accounts, collateralized loans, and various rewards through its native token, CEL. It aimed to provide high yields with low risk by positioning user "deposits" as unsecured loans to the organization. Celsius generated revenue by lending these deposits to institutional borrowers and sharing the interest with depositors. The platform's user-friendly approach, transparency, and community focus set it apart from traditional financial institutions and other crypto platforms.

Celsius managed a variety of crypto assets, with a focus on Ethereum and Bitcoin balances. The business model relied on aggressive asset management in the crypto markets, often involving significant off-chain operations. The company incentivized user engagement and loyalty through its CEL token, creating multiple revenue streams.

2.3. Account and transaction types within the Celsius Data

By the end of Celsius' run there were three main types of accounts that customers funds could be found in: Earn, Custody or Withhold. Customers could perform around seven main transaction types: Deposit funds, earn interest, transfer funds, swap cryptocurrencies, make a loan payment, make a loan interest payment, or add collateral.

1. Accounts
    (a) Custody- Coins in your Custody account can be transferred, swapped, or used as loan collateral, but they don't earn rewards.
    (b) Earn- Coins in your Earn account earn interest and can only be transferred to your Custody account.
    (c) Withhold - where investments by unaccredited investor customers residing in nine states in which Celsius did not have the proper licenses to offer a Custody program went.
2. Transaction Types
    (a) Collateral- Coins that served as collateral for Celsius loans.
    (b) Deposit- Bringing in new money or cryptocurrency from the outside into Celsius' platform
    (c) Interest and Rewards- Amount of interest or rewards earned on coins in the Earn account. Either in same currency as coins or in CEL tokens.
    (d) Transfer- Transferring of coins between Custody and Earn accounts.
    (e) Loan interest Liquidation
    (f) Loan interest Payment- Payment made to service the loan interest.
    (g) Loan Principal Payment - Loan principal repayment.
    (h) Loan Principal Liquidation

(i) Operation Cost

(j) Swap - Exchange of one cryptocurrency for another. e.g. ETH for BTC

(k) Withdrawal- Withdrawal of currency.

Originally, all customer funds that came in were put into a main wallet. Due to regulations starting April 15th 2022 Celsius was forced to create separate accounts depending on the customer. If the customer sent money to the Celsius platform that money was first supposed to go into a custody account. According to Celsius' FAQ Coins in your Custody account can be transferred, swapped, or used as loan collateral, but they don't earn rewards. Purchased or transferred coins will go to your Custody account. If a customer wanted to take advantage of the Earn program to earn interest on their deposit then they would need to transfer the coins to an Earn account. In the Earn account "Coins [would] earn rewards but cannot be swapped or used as loan collateral. Coins in your Earn account can only be transferred to your Custody account." The Withhold account was where investments by unaccredited investor customers residing in nine states in which Celsius did not have the proper licenses to offer a Custody program went. Celsius blocked customers in these states from making further deposits to the Earn program, and instead designated post-April 15, 2022 transfers as being made to newly-designated "Withhold accounts." [1]

For those customers whose deposits were not put into a Withhold account there were numerous transactions available to them and reflected in the data. You could deposit money into your custody account which meant bringing in new money or cryptocurrency from the outside into Celsius' platform. You could transfer money between your Earn account and your Custody account. Customers who no longer wished to earn interest on the money would transfer that money out of the Earn account and into the Custody account. Similarly if a customer wanted to earn interest in either Cel tokens or the currency invested they would transfer that amount from the custody account to the Earn account. Another option was

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

available to customers and that was swapping cryptocurrencies. So if you wanted to swap your ETH for BTC you could do that on Celsius platform within a Custody account. Within your Earn account customers were only allowed to earn interest or transfer money in and out according to Celsius website.

Celsius had additional features for customers that included the ability for customers to take out loans. As with standard loans collateral was required due to the volatile nature of cryptocurrency. Coins deposited into a Custody account could be used for loan collateral. Customers who took out a loan would also need to make loan principal and loan interest payments to Celsius.

In the data provided by the bankruptcy proceedings we see that what Celsius claimed about the accounts is not entirely true. In fact, we see that there are a few transactions from the Withhold accounts that are loan interest payments, loan principal payment, and Collateral. Similarly, in the Earn account you see the same loan and collateral transactions along with Withdrawals, swapping of cryptocurrency, and the standard deposit and transfers into the Earn account. So within the data there is not the distinction of transactions between the Earn and Custody accounts as Celsius would claim in their FAQs.

2.4. Timeline of Celsius Deposit Run

Celsius launched its crypto asset-based finance platform in March 2018, marking the beginning of its primary financial product, the "Earn" program. This program allowed customers to deposit cryptocurrencies on Celsius's platform, where they could either earn interest or borrow dollars against their deposited assets. The initial release of Celsius's mobile application followed in June 2018, accompanied by the marketing slogan "Unbank yourself," promoting the innovative financial opportunities available to users.

From the platform's inception until April 14, 2022, Celsius's operations were governed by a series of Terms of Use. These terms underwent eight revisions from the original date of February 1, 2018. Notably, from September 29, 2020, the terms specified that by participat-

ing in the Earn program, customers transferred "all right and title" of their crypto assets to Celsius. This provision allowed Celsius to pledge, lend, or otherwise utilize these assets at its discretion.

In an effort to comply with regulatory requirements, Celsius developed a Custody program tailored for its unaccredited U.S. customers, which was announced on April 11, 2022, and officially launched on April 15, 2022. This program required U.S. customers to transfer their assets to Custody accounts, which continued to earn rewards but were distinct from the Earn program accounts. To implement this transition, Celsius reallocated crypto assets from its Main wallets to Custody wallets. However, the infrastructure did not treat specific assets as belonging to individual customers, leading to aggregate transfers and a need for manual reconciliation.

Celsius's Custody program required frequent manual reconciliation of Custody wallet holdings against account balances, a process performed 53 times between April 20, 2022, and July 12, 2022. Despite these efforts, the Custody wallets experienced shortfalls on 16 occasions during this period, necessitating the transfer of assets from Main wallets to cover deficits. Conversely, excesses were transferred back to Main wallets.

In May 2022, Celsius encountered significant liquidity challenges, with board minutes revealing that the company's capital was nearly depleted. Customer withdrawals between May 9 and May 24 resulted in a net asset loss exceeding $1.4 billion. By June 12, 2022, Celsius's liquidity constraints led to the suspension of all withdrawals, citing "extreme market conditions." Despite the withdrawal pause, customer account balances in both Custody and Earn programs continued to rise due to ongoing transfers into the platform.

As liquidity issues persisted, Celsius faced a growing deficit in its Custody wallets. On June 28, 2022, Celsius initiated asset transfers totaling approximately $47.9 million to mitigate these deficits. Nevertheless, by the time Celsius filed for bankruptcy on July 13, 2022, these deficits reemerged, culminating in a deficit of approximately 3.2 million coins ($16.9 million) in Custody wallets by October 28, 2022.

The evolution of Celsius's Terms of Use culminated in a significant change with the introduction of the Custody program. Unlike prior versions, the new terms specified that assets in Custody wallets remained the property of customers, marking a pivotal departure from Celsius's previous stance where it retained full rights over deposited crypto assets.

Celsius had approximately 1.7 million users in 2021. Beginning in early 2022, while many cryptocurrencies were still close to all-time highs, Celsius began to experience withdrawals. Liquidity continued to deplete and rumors began to spread about insolvency concerns. At the time, Celsius chose to limit some user's ability to withdrawl. Then, two months later, Celsius implemented a full freeze on withdrawals before filing for bankruptcy , and eventually filing for bankruptcy. This event raised concerns about the stability and resilience of digital asset markets, as well as the potential risks associated with the actions of insiders and influencers in this space. At the time, Celsius was the third crypto company to file for bankruptcy. Below we highlight the key dates:

2017: Celsius Network Founded

March 2018: Celsius launches crypto asset-based finance platform and raises $50 million with ICO of the CEL digital currency.

June 2018 : Initial release of Celsius's mobile application

April 12, 2022: Celsius Network gave advanced notice to its community of a change to its U.S. platform that would begin on April 15, 2022. Specifically, Celsius would be launching a new Custody solution for non-accredited U.S. investors such that they could continue to swap, borrow, and transfer within their account, but they could no longer add new assets and earn rewards (i.e., yield) on Celsius' Earn platform.

May 7-12, 2022: The rapid, collapse of the $40 billion algorithmic stablecoin Terra (UST) and its companion token LUNA shocked cryptocurrency markets.

June 12, 2022: Celsius freezes withdrawals, swaps and transfers in response to extreme market conditions. The company reveals no timeline to restore user services.

June 30, 2022: Celsius hires restructuring experts to explore the firm's options.

July 13, 2022: Celsius files for bankruptcy attributing its liquidity challenges to contagion from the UST-LUNA collapse. SEC Charges Celsius Network with Fraud and Unregistered Offer and Sale of Securities

3. Data and Empirical Design

3.1. Data

To analyze the impact of the Celsius Network deposit run on tokenholders, we utilize a comprehensive dataset that includes transaction data and wallet holdings of both Celsius and non-Celsius tokenholders from April 14, 2022, to June 12, 2022, the date when withdrawals were halted. We merge these data with demographic information based on the name of Celsius tokenholders in bankruptcy filings, which describe below. This rich dataset enables us to examine the relation between the decentralized deposit run and the consequences for various user groups.

3.1.1. Demographic Characteristics

A non-redacted version of the Celsius bankruptcy filings revealed the names and token holdings of all account holders. To identify the gender and ethnicity of the account holders, we used the following approach.

To identify gender, we developed an algorithm that uses the names from the bankruptcy filing and three different methods to predict gender based on first names. Our primary data source is the University of California-Irvine's "Gender by Name" dataset, which we iteratively augment with two additional programs (Global Gender Predictor and Gender

Guesser) when a first name does not match a gender.[2] Using these combined algorithms, we successfully match gender for 87% of the names in the Celsius bankruptcy filing with high confidence.

To identify the ethnicity of individuals, we employed a Python script utilizing a combination of three different methods and the names from the bankruptcy filing. First, we used the "Ethnicity" class to create dictionaries and obtain initial ethnicity guesses for the names from the bankruptcy filing. Second, we applied a pre-trained model from "EthnicClassifier" to classify names into specific ethnic groups, mapping the results to more readable ethnicity labels. Third, we utilized the "RaceBERT" model to predict ethnicity. The final ethnicity assignment was determined by integrating the results from these three methods. If the initial guess matched the second classifier's result and the third did not indicate African or Nordic ethnicity, we retained the initial guess. For discrepancies, we considered specific conditions to assign 'African' or 'Nordic' as appropriate, or made adjustments based on the combination of results. Additionally, we standardized any 'Arabic' results to 'arabic/middle eastern.'[3] Our multifaceted approach identifies ethnicity for 91% of the sample with high confidence.

[2]The *first* program is the University of California-Irvine's "Gender by Name", from the UCI Machine Learning Repository, available at https://doi.org/10.24432/C55G7X. This dataset links first names to genders, providing counts and probabilities, using open-source government data from the US, UK, Canada, and Australia. When these data do not return a match, we use a *second* program titled, "Global Gender Predictor," which predicts gender (male, female, unknown or unisex) from first names based on the World Gender Name Dictionary 2.0, which includes over four million unique names. This package is described at https://github.com/attract-ai/global-gender-predictor. When the gender is still unknown or unisex, we use a *third* package titled "gender-guesser" and available at https://pypi.org/project/gender-guesser/. This package is based on program titled "gender" by Jorg Michael and described at https://www.autohotkey.com/board/topic/20260-gender-verification-by-forename-cmd-line-tool-db/.

[3]The first name-ethnicity classifier is "Ethnicity." The second model, "EthnicClassifier," is from the python program "ethnicseer," which determines the ethnicity of a name using linguistic features like character sequences and phonetic pronunciation. It includes a pre-trained model that can identify 12 ethnicities: Middle-Eastern, Chinese, English, French, Vietnamese, Spanish, Italian, German, Japanese, Russian, Indian, and Korean, with an accuracy of around 84% on the test dataset. See https://github.com/pucktada/ethnicseer. The third classifier is RaceBERT, predicts race and ethnicity from names using a transformer-based model. It categorizes race based on U.S. census classifications (e.g., non-Hispanic White, Hispanic, non-Hispanic Black) and provides detailed ethnicity predictions such as Greater European, British, and Asian, Indian Sub Continent. See https://pypi.org/project/racebert/.

3.1.2. Etherscan Transactions and Holdings

We used 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 encompassed pulling snapshots of the wallet holdings at a specific block height corresponding to a calendar day for all days in 2022. 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. Moralis has multi-chain capabilities, so this allows us to pull data on any token holding on Ethereum mainnet, including all relevant ERC-20 token transactions, as well as other popular layer-1 chains.

3.1.3. Classifying Token Risk and Purpose

Moralis has its own token risk measure that ranges from 1 to 99 with 99 being the least risky. Digital assets like ETH have a risk rating of 99 in Moralis. We also had a research assistant manually look up addresses and token names to classify tokens. This process allowed us to classify risk into high, medium, and low. High risk projects were anything associated with memecoins, gaming, gambling or generally had a gamification element and finally, derivatives or anything that allowed for outsized speculation via leveragae. Low risk projects were all L-1s and stablecoins regardless of if they were fiat-backed, crypto-backed or some hybrid combination. Medium risk tokens were anything not classified as low risk or high risk.

The RA also created a description of the token and/or business purpose of the token. We used this to classify the projects into three broad categories as well as several subcategories within the project. The broad categories included DeFi tokens, infrastructure tokens, and Web3 tokens. Within the broad categories, DeFi subcategories included DEXs, lending protocols, yield farming protocols, liquidity and insurance products. Within the infrastructure tokens were data, layer-2s, ZK-proof rollup protocols, oracles, and protocols enabling bridges

and cross-chain capabilities. Web3 tokens included subcategories like gaming, social, public goods, collector circles, and educational.

3.1.4. Wallet Concentration and Diversification

To understand whether particular wallets concentrate on certain token types and risk levels, we calculate a Herfindahl-type index of token holdings. We also calculated risk-adjusted wallet returns, Sharpe ratios, and crypto-factor adjusted returns (Liu et al., 2022). To better understand the level of sophistication of the wallet we examine their strategic trades relative to more patient capital and bank-like holdings. Specifically, we look at trading frequency by token type, average holding periods, and portfolio turnover.

3.2. Empirical Design

We estimate three regressions to understand whether the digital deposit run at Celsius led to a sudden and significant shift in the allocation of capital in the wallet. Specification (1) is a standard difference-in-differences specification with fixed weekly effects. Specification (2) also includes wallet-fixed effects. Specification (3) includes fixed effects for the wallet and week and controls for characteristics of the wallet that vary over time. For example, our difference-in-differences regression specification (3) is detailed below.

$$Y_{it} = \alpha + \beta \left(Treat \times Post\right)_{it} + \mu X_{it} + \gamma_i + \rho_t + \varepsilon_{it} \tag{1}$$

In the above equation, Y represents the outcome variable, such as the quantity of stablecoins held in a wallet i in week t. $Treat$ indicates wallets involved in Celsius transactions before April 2022. $Post$ indicates either the beginning or the end of the Celsius deposit run. β is the main coefficient of interest that isolates the change attributable to the digital deposit run. γ_i denotes the wallet-fixed effects that capture all of the wallet-level time-invariant effects, and ρ_t represents a weekly-fixed effect that attempts to control for crypto market

trends over time. X_{it} represents a vector of controls for wallet characteristics that include the depth of experience with crypto, such as total wallet balance and turnover.

3.3. Dependent variables

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 will be measured. Adding *deposits* to the initial holdings accounts for any additional funds or assets placed into the account after 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 non-zero stranded assets.

4. Results

4.1. Depositor Demographics

Table 1 provides an overview of the demographic diversity within the Celsius Network's depositor base, offering insights into the composition of its users by type, gender, and ethnicity. The total number of depositors in the dataset is 395,523, providing a substantial sample size for demographic analysis. Across depositor types, 99.5% of observations are individuals, while only 0.5% are institutions. This shows that the vast majority of Celsius depositors included in bankruptcy are individuals, with institutions making up a small fraction of the

total depositor base.

[Insert Table 1 here]

The gender distribution indicates a predominance of male depositors (74.5%) included in the bankruptcy filings, with females (20.0%) and those whose gender is unknown (5.8%) constituting smaller proportions.

The ethnic distribution shows a diverse depositor base at Celsius, with Anglo-Saxon depositors being the largest group (27.8%). German (12.9%), Hispanic (9.3%), French (9.0%), Italian (8.9%), and Chinese (7.3%) ethnicities also have significant representations. Our script fails to identify ethnicity for only 8.9% of the sample.

4.2. Properties of Earn Accounts

Table 2 presents the summary statistics for Earn Accounts on the Celsius Network, categorized into three sections: token holdings, transaction behaviors, and account balances.

On average, Earn Accounts hold 3.6 tokens, with a median of 3 tokens. Approximately 88% of accounts hold BTC, and 52% of accounts hold ETH. About 13% of accounts hold stablecoins, while 67% of accounts hold other types of tokens.

[Insert Table 2 here]

For transactions, approximately 20% of accounts have incoming transactions during our sample period. The average incoming Bitcoin value is around $14,000, with a high standard deviation of $173,000. The median incoming Bitcoin value is only $895, which reflects a skewed distribution. The average incoming Ethereum value is $16,700 with a $328 median, while the mean incoming stablecoin value is $18,100 with and a median value of $1,500. Other incoming tokens average $9,800 with a median of $139.

Approximately 30% of accounts have outgoing transactions. The mean outgoing Bitcoin value is $14,900 with a median value of $1,700. Outgoing Ethereum averages $21,600 with a

median outgoing value of $552. Outgoing Stablecoin (USD): The mean outgoing stablecoin value is $20,900 with a median value of $1,100. Other outgoing tokens average $10,300 with a median of just under $150.

For interest earned, the total mean interest earned is $149, with a median of $13. Interest earned from Bitcoin has a mean of $51 and a median of $3. Interest from Ethereum shows a mean of $103 and a median of $6. Interest from stablecoins averages $131, with a median of $1. Other interest earned averages $84.06, with a median of just over $2.

Regarding balances, the mean initial holdings of the earn accounts (Bitcoin + Ethereum + USDC) are $24,000, with a median initial holding of $901. The mean stranded asset ratio is 0.85, with a median value of 1.00.

Figure 1 graphs the daily outgoing and incoming values of Earn Accounts for Celsius Networks during our sample period. It reveals a pronounced peak in withdrawals around mid-May 2022, where the outgoing value surpasses $600 million. 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.

[Insert Figure 1 here]

Overall, this figure shows the volatility in the transaction values of earn accounts, highlighting a significant withdrawal event in mid-May and subsequent variations in both withdrawals and deposits. This trend indicates periods of high user response to external events affecting Celsius Networks during this time frame.

Figure 2 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. Thus, there is also a sizable fraction of accounts with large holdings, although it is noticeably smaller than the lowest range.

[Insert Figure 2 here]

Regarding the distribution across ranges, Figure 2 shows a sharp decline in the fraction of accounts as initial holdings increase. Each subsequent range (i.e., from \$10,000–\$20,000, \$20,000–\$30,000, etc.) has progressively fewer accounts. This distribution suggests that most Celsius Network users start with relatively small investments, with a minority holding substantially more significant initial amounts. The data highlights the variation in user investment levels within the network.

4.3. Stranded Assets and Depositor Demographics

Table 3 examines the relation between various demographic characteristics and two key metrics: the *Stranded Asset Ratio* and the *Stranded Asset Indicator*. We present these tests with and without controls, which are individual fixed effects.

[Insert Table 3 here]

Overall, the analysis highlights significant demographic disparities in the extensive and intensive margins of stranded assets, with the effect being more pronounced for certain ethnic and gender groups. Specifically, we find a negative and statistically significant relation between being male and both the *Stranded Asset Ratio* and the *Stranded Asset Indicator*, suggesting that males are less likely to be associated with stranded assets.

Similarly, individuals of German, French, Italian, Chinese, and African descent also exhibit significant relations with these metrics, though the direction of these relations varies. Notably, individuals of Hispanic, Indian, Russian, and Arabic descent show positive and significant coefficients, indicating both a higher likelihood of association with stranded assets and having larger amounts of assets tied up.

4.4. Stranded Assets and Monitoring Incentives

Table 4 investigates the relation between monitoring incentives, specifically institutional involvement, and the likelihood of having stranded assets at Celsius. The table presents regression results across eight models, where the dependent variables are the stranded asset ratio and a binary indicator for having stranded assets.

[Insert Table 4 here]

Institutional presence is associated with a significant reduction in the stranded asset ratio across all models. For instance, in Model (1), the coefficient of-0.127 suggests that institutions decrease the stranded asset ratio by 12.7 percentage points. Even with additional controls in Model (4), the negative relation persists, albeit at a smaller magnitude (-0.0433). Similarly, institutions consistently reduce the likelihood of being classified as having stranded assets, with coefficients ranging from -0.106 in Model (5) to -0.0431 in Model (8), all statistically significant at the 1% level.

The variable *Log(1+Initial Holdings)* also shows a significant negative impact on both the stranded asset ratio and the stranded asset indicator, suggesting that larger initial holdings are associated with a lower likelihood of having stranded assets.

Taken together, these findings suggest that institutional investors are more sophisticated in mitigating the risk of having stranded assets at Celsius, likely due to better monitoring capabilities.

4.5. Stranded Assets and Wallet Transactions

Table 8 presents the results of a regression analysis examining the effect of a *Post* $\times$ *Stranded asset indicator* condition on various types of cryptocurrency transactions. The table includes five 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 DeFi transactions (column 3), the number of NFT transactions (column

4), and the number of other transactions (column 5). We estimate these regressions using OLS with individual and week fixed effects for just over 185,000 observations.

[Insert Table 8 here]

In column 1, the coefficient on *Post* × *Stranded asset indicator* is positive (0.070) and statistically significant (p <0.01), indicating that users with stranded assets increase the number of transactions on Celsius after having withdrawals halted. Similarly, we observe a significant increase in *Send/Receive* transactions, where the coefficient on the interaction term is 0.063 (p <0.01).

The relation between *Post* × *Stranded asset indicator* and DeFi transactions, however, is essentially zero (−0.000) and not statistically significant, as is the relation with NFT transactions (−0.001). The relation on other types of transactions is positive (0.008) but not statistically significant.

Overall, these findings suggest that having stranded assets after Celsius began limiting withdrawals is linked to an increase in the number of wallet transactions and Send/Receive transactions. However, the relation with other transactions like DeFi and NFT is minimal or non-existent.

4.6. Stranded Assets and Token Transfer Activity

Table 6 shows the results of a regression analysis investigating the relation between having stranded assets after Celsius began limiting withdrawals and sending or receiving Ethereum (ETH) and ERC-20 tokens. Similar to other regressions, we account for individual and weekly fixed effects.

[Insert Table 6 here]

Column 1 shows that Celsius users with stranded assets are more likely to send ETH tokens, as evidenced by the positive (0.010) and significant (p <0.01) coefficient on the interaction term, *Post* × *Stranded asset indicator*. However, in column 2, there is a statistically

significant decrease in the receiving of ETH for users with stranded assets in the post period, with a coefficient of -0.009 on the interaction term that is significant at the 1% level.

For ERC-20 tokens, Celsius users with stranded assets exhibit a significant increase in both sending and receiving in the post period, with increases of 0.003 (p <0.05) and 0.004 (p <0.05), respectively.

Together, these findings suggest that restricting withdrawals for users with stranded assets has a significant and differentiated impact on the sending and receiving of ETH and ERC-20 tokens. While the condition leads to an increase in the sending of ETH, it reduces the receiving of ETH. In contrast, both sending and receiving of ERC-20 tokens increase under the same condition.

4.7. Stranded Assets and Token Riskiness

Table 7 presents the results of a regression analysis that examines the effect of the *Post* × *Stranded asset indicator* condition on the receiving of different types of tokens categorized by their risk level. The analysis is divided into three columns, corresponding to the receipt of stablecoins (column 1), Low-Risk Tokens (column 2), and High-Risk Tokens (column 3). All unique digital asset was hand-coded to identify risk. Two RAs hand-coded over 1000 digital assets. They had to read the business description and check out the websites. If there was a disagreement, one of the researchers intervened to be the decisive vote. In general, stablecoins and other established L-1s are considered low risk, while medium risk contains many common DeFi projects as well as up-and-coming projects. High-risk was used for meme coins and any project that looked like a scam, did not have a legitimate business model, and/or offered seemingly egregious levels of leverage or speculation. The regression controls for individual and week fixed effects.

[Insert Table 7 here]

The results indicate that the *Post* × *Stranded asset indicator* condition has no statistically

significant relation with the receipt of stablecoins, as shown by the coefficient of −0.0001, which is not significant. Similarly, the relation with the receipt of *Low-Risk Tokens* is positive but not statistically significant.

However, *Post* × *Stranded asset indicator* does have a statistically significant relation with the receipt of *High-Risk Tokens*, with a positive coefficient of 0.0041 (p <0.01). This result suggests that users with stranded assets have an increased receipt of High-Risk Tokens after Celsius began limiting withdrawals as compared to the prior period.

Overall, these findings suggest that users with stranded assets shift towards receiving high-risk tokens but do not change their use of stablecoins or low-risk cryptocurrencies.

4.8. Stranded Assets and Wallet Descriptives

Having established how users with stranded assets altered their transaction patterns and token choices for buying and selling, a natural question is how these behavioral changes manifested in their overall wallet composition and risk exposure. To investigate this, we examine various wallet-level metrics, including concentration (HHI), various measures of risk, returns, and Sharpe ratios.

[Insert Table **??** here]

Specifically, Table 8 presents difference-in-differences estimates examining how having stranded assets affects wallet characteristics. In column 1, we observe that wallets with stranded assets experienced a significant decrease in wallet concentration (coefficient = -0.00417, p¡0.01), suggesting these users may have sought to diversify their crypto holdings after being impacted by the withdrawal freeze.

Consistent with the transaction data, we observe that these same wallets increase the quality of their holdings as evidenced by higher MOralis-derived risk scores where higher ratings indicate superior quality (column 2, coefficient = 0.00924, p¡0.01). Because Moralis only provides ratings for the most prominent coins, this externally derived risk score does

not represent the whole crypto market. In fact, as we see in column 3, wallets simultaneously exhibit the worst risk scores (column 3, coefficient = -0.00679, p¡0.01) when we consider our more comprehensive hand-coded sample based on project descriptions. This suggests the wallet may be balancing some more conservative high-end coins with efforts to camble for resurrection through less prominent coins such as meme coins or emergent DeFi tokens.

The most striking result appears in column 4, where the average daily returns of the wallets with stranded assets increased substantially (coefficient = 0.105, p¡0.01). This higher return, however, does not translate into better risk-adjusted performance, as evidenced by the insignificant coefficient in the Sharpe ratio in column 5 (coefficient = 0.000184, not statistically significant). This pattern suggests that, while these wallets achieved higher raw returns, they did so by taking on proportionally more risk. This is consistent with the notion of gambling for resurrection highlighted in the behavioral literature.

Therefore, in Panel B, we turn to examining some specific categories of tokens held and their changes before and after the inability to withdraw assets. We find the wallet is holding more tokens in the highest risk category, such as meme tokens, while simultaneously holding more stablecoins.

Overall, these findings suggest that having stranded assets after Celsius began limiting withdrawals is linked to a change in behavior after the experience.

5. Policy Discussion

Our evidence suggests that those who trusted the espoused "bank-like" features of Celsius Network were being duped by cheap talk. As a result, retail investors, rather than institutional investors, were more exposed to the fallout. Similarly, more vulnerable demographic groups, such as women, were more exposed. This suggests that regulation changes may be necessary to protect retail depositors of digital assets. Typically, disclosure regimes help mitigate informational asymmetries (Howell et al., 2020) and this was certainly the case

during the ICO craze, but increasingly, regulators are saying even disclosure is not enough for retail investors when financial literacy rates are so low (Lusardi and Mitchell, 2014).

Therefore, considering the collective evidence, we highlight a few paths regulators could explore: (i) refining the definition and regulatory requirements of a "decentralized" bank, (ii) experimenting with a digital asset equivalent of deposit insurance, and/or (iii) placing the burden on the decentralized entity to demonstrate adequate user education to use the service and/or more advanced financial sophistication to make large deposits. We consider each in turn.

First, why was the cheap talk so successful? Was it simply a case of false advertisement, and therefore, are the rules from the Federal Trade Commission sufficient to protect consumers, or does something more need to be done? Given our evidence, it appears something more needs to be done. The risk and complexity created by Celsius Network's holdings (i.e., primarily illiquid digital assets) were confusing and not adequately disclosed. Therefore, we suggest more precise definitions of what constitutes a decentralized "bank." If the entity under consideration qualifies as a decentralized bank, then presumably, the decentralized "bank" should also be required to participate in a risk disclosure regime, capital adequacy requirements, and stress testing. Recognizing that there are distinctions between centralized and decentralized banking entities, a regulator may further want to consider adapting more traditional definitions of capital tiers to the digital asset context. For instance, stablecoins could receive a different classification than other tokens that the "bank"-like entity may possess.

Another natural extension of existing regulation in the United States that could at least partially remedy a failure like that witnessed for Celsius Network is to require deposit insurance for the deposits into a decentralized "bank." Of course, this leads to a natural question of how to implement deposit insurance schemes for digital asset platforms. Should the insurance regime be similar to the traditional banking system where tax dollars fund it, or should digital asset contributions to public goods fund the regime? Or, would it make sense

to adopt a mandatory yet private approach to insurance markets in the digital asset realm similar to what has been done in healthcare markets? Ideally, to move in one direction or the other, one would have evidence on how insurance influences user behaviors and platform stability and the extent to which the specific provider of the insurance matters. A potential solution in this space then is to think about piloting a program where small amounts of insurance are offered randomly to assess the efficacy in the digital realm.

Third, based on our analysis of user behavior and demographics, more educationally based policies might be proposed. For instance, following some high-profile suicides in the wake of the meme stock craze, trading platforms like Robinhood voluntarily established limits on retail investors' activity based on financial literacy. One could implement a parallel yet mandatory approach. Like Robinhood, you cannot trade options without taking a quiz first; users wouldn't be able to use more sophisticated Earn products without taking a quiz. Another educational approach may require risk-based education or cooling-off periods after extreme volatility to prevent gambling for ressurection-like activities. Given the smart contract nature of many of these protocols, embedding mandatory risk training seems highly feasible at a low cost. Moreover, the mandatory training should not be very long as evidence suggests financial literacy can be achieved with simple rules-of-thumb (Drexler et al., 2014).

6. Conclusion

This study provides novel insights into the dynamics of digital asset 'bank runs' and their association with retail investor outcomes by examining the collapse of the Celsius Network. Our findings suggest significant disparities in exposure to stranded assets across demographic groups, with retail investors and certain ethnicities appearing more likely to have stranded assets. Institutional investors exhibited patterns consistent with superior risk management, potentially due to more effective monitoring capabilities.

The behavioral patterns following the Celsius collapse varied among users, with those

holding stranded assets showing a tendency to shift away from DeFi and NFT transactions towards more basic cryptocurrency operations. Notably, we observed patterns consistent with gambling for resurrection behavior, as evidenced by increased holdings of high-risk tokens among users with stranded assets.

These results have important implications for policymakers and regulators in the digital asset space. Our findings suggest the need for more robust regulatory frameworks that may better protect retail investors from the risks associated with pseudo-banking services. Potential policy directions include refining the definition and regulatory requirements for decentralized banking entities, exploring digital asset deposit insurance schemes, and considering mandatory user education and financial literacy requirements.

Future research could extend this work by examining the potential efficacy of proposed regulatory measures in mitigating risks in the digital asset markets. As digital asset markets continue to grow and evolve, understanding and addressing these challenges will be crucial for fostering a more stable and inclusive digital financial ecosystem.

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Appendix A: Additional Tests

Earn Account Deposits and Withdrawals By Token

To gain a deeper understanding of user behavior and the flow of assets within the Celsius platform during a critical time frame, 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 BTC, ETH, USDC, and other alternative tokens (ALT). The data reveals significant spikes, particularly in mid-May 2022, when all tokens experienced a sharp surge in withdrawals, with ALT tokens peaking at nearly $200 million USD. Following this peak, withdrawal activity generally declined but showed a resurgence in early June, especially for ETH.

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 $40 million USD. Notably, BTC and ALT 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.

Location Summary Stats

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.

Transactions Summary Stats

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 23 specific tokens along with a category for "40 other tokens."

[Insert Table A2 here]

Bitcoin (BTC) leads with the highest number of transactions, totaling 773,204, and a transaction value of $4,819.65 million. Ethereum (ETH) follows with 466,290 transactions and a total value of $4,207.64 million. USDC, a stablecoin, also shows significant activity with 424,202 transactions and a transaction value of $3,309.16 million.

CEL, the native token of the Celsius platform, has 214,630 transactions with a total value of $215.76 million. MATIC and ADA have 130,856 and 119,510 transactions, with values of $230.09 million and $322.65 million, respectively. Other notable tokens include USDT with 80,536 transactions and a value of $601.46 million, LINK with 67,799 transactions valued at $151.00 million, and SOL with 58,312 transactions worth $127.89 million.

In the lower range, tokens such as BCH and AAVE have fewer transactions (22,033 and 23,832, respectively) with lower transaction values ($20.69 million for BCH and $15.24 million for AAVE). The category for "40 other tokens" aggregates 252,421 transactions with a total value of $715.68 million.

Overall, the table highlights the dominance of BTC, ETH, and 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 presents a comprehensive analysis of transactions across different account types on the Celsius platform, categorized into Custody, Earn, and Earn - Interest accounts. Each account type exhibits significant transactional activity, reflecting the diverse operations of the platform.

[Insert Table A3 here]

Custody accounts recorded 529,054 transactions, amounting to $6.1 billion. Within this category, incoming transactions such as internal account transfers and deposits are notable, with values of $2.1 billion and $744 million, respectively.

Outgoing transactions, particularly withdrawals and internal account transfers, also represented significant sums, totaling $1.8 billion and $461 million, respectively. These figures indicate the substantial movement of assets within Custody accounts, both in and out of the platform.

Earn accounts showed even more robust activity, with 929,770 transactions totaling $8.5 billion. Incoming transactions were led by deposits and collateral, contributing $1.2 billion and $959 million, respectively. On the outgoing side, withdrawals and internal account transfers were the most significant, with values of $2.6 billion and $2.3 billion, respectively. This data highlights the prominence of Earn accounts in the Celsius ecosystem, with large volumes of transactions related to both deposit activities and withdrawals.

The Earn - Interest accounts displayed a vast number of transactions—1,506,639 in total—but with a relatively lower transaction value of $81 million. This suggests that these transactions, which likely involve the distribution of interest payments and rewards, are smaller in size but frequent. The large number of transactions highlights the role of Earn - Interest accounts in maintaining user engagement through regular interest distributions.

In summary, the table illustrates the scale and variety of transactions on the Celsius platform, with Earn accounts showing the highest transaction volumes and values. Custody

accounts also play a critical role, particularly in facilitating large asset movements, while Earn - Interest accounts focus on frequent, smaller transactions related to interest payments.

Demographics and Token Holdings

Table A4 provides insights into the relation between demographic characteristics and various aspects of cryptocurrency holdings and usage. The table explores several dependent variables, including the logarithm of the number of tokens held and the likelihood of using specific types of cryptocurrencies, such as BTC, ETH, stablecoins, and alternative coins (ALT).

The results in the first column reveal significant demographic effects on the number of tokens held. Being male is associated with a significant increase in the number of tokens held (coefficient = 0.590, $p < 0.01$). Ethnic groups such as Anglo-Saxon, French, Chinese, Indian, and Arabic also show positive and significant coefficients, indicating a higher number of tokens held compared to other groups. In contrast, German, Hispanic, Italian, Russian, and African demographics are associated with significantly fewer tokens held.

The second column shows that males are slightly less likely to use Bitcoin (coefficient = -0.0120, $p < 0.01$). Anglo-Saxon and French individuals also show a negative association with Bitcoin usage. In contrast, demographics such as German, Hispanic, Italian, Chinese, and Indian show a positive and significant likelihood of using Bitcoin.

The third column highlights that males are more likely to use Ethereum (coefficient = 0.0813, $p < 0.01$). Anglo-Saxon, Hispanic, German, Italian, Russian, and African demographics have a negative association with Ethereum usage, whereas Chinese, Indian, French, and Arabic groups are positively associated with its use.

The fourth column demonstrates that males are more likely to use stablecoins (coefficient = 0.0249, $p < 0.01$). Anglo-Saxon, Hispanic, French, Italian, Russian, and African demographics have a significant negative association with stablecoin usage, while German, Chinese, Indian, and Arabic demographics show a positive association.

The fifth column reveals that males are more likely to use alternative coins (coefficient = 0.0844, $p < 0.01$). Anglo-Saxon, German, Hispanic, Italian, Russian, and African demographics show a significant negative association with using alternative coins. In contrast,

French, Chinese, Indian, and Arabic groups are positively associated with alternative coin usage.

[Insert Table A4 here]

Overall, these results suggest that demographic factors significantly influence both the number of tokens held and the types of cryptocurrencies individuals are likely to use. Males generally hold more tokens and are more likely to use various types of cryptocurrencies, whereas certain ethnic groups show distinctive patterns in cryptocurrency usage, with some being more inclined towards specific types of cryptocurrencies and others less so.

Monitoring Regressions Without Small Accounts

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 is the *stranded asset ratio* for accounts with initial holdings greater than \$1,000 and \$10,000 USD, separately.

[Insert Table A5 here]

In columns (1) and (2), the analysis includes a broader sample of observations (194,032), while columns (5) and (6) focus on a smaller sample (95,472). The results indicate a statistically significant negative relation between the presence of institutional investors and the stranded asset ratio, as evidenced by the coefficients on the *Institution* variable, which are -0.0609 and -0.0671 in columns (1) and (2), respectively, and -0.0320 and -0.0424 in columns (5) and (6), respectively. These findings suggest that institutional presence is associated with a lower likelihood of stranded assets.

The *Log(1+ Initial Holdings)* variable also shows a significant negative relation with the *stranded asset ratio* across all models, with coefficients ranging from -0.011 to -0.005. This indicates that larger initial holdings are associated with a reduced likelihood of stranded assets.

Overall, the results highlight the importance of monitoring incentives in mitigating the presence of stranded assets for Celsius users, particularly among accounts with larger initial holdings.

On-Chain Transactions

Table A6 provides summary statistics for various on-chain transaction activities. The data comprises 185,185 observations, and the table reports the mean and standard deviation (SD) for each type of transaction.

[Insert Table A6 here]

The average number of on-chain transactions per account is 0.549, with a standard deviation of 1.94, indicating considerable variation in transaction frequency across accounts. The mean value for *Send/Receive Transactions* is 0.467, suggesting that most on-chain activities involve basic transfers of assets. This category also shows significant variability, as indicated by the standard deviation of 1.63.

Transactions involving decentralized finance (DeFi) and non-fungible tokens (NFTs) are relatively rare, with mean values of 0.028 and 0.008, respectively, reflecting their specialized use cases. The remaining transaction types, grouped under *Other Transaction*, have a slightly higher mean of 0.045.

For specific asset movements, sending ETH is slightly more common (mean of 0.094) than receiving ETH (mean of 0.072). Similarly, sending and receiving ERC-20 tokens have low mean values of 0.013 and 0.026, respectively. However, sending and receiving ETH has a notably higher standard deviation than sending and receiving ETH-20, indicating more sporadic activity.

Stablecoin token transactions are relatively infrequent, with mean values for receiving such tokens at 0.02, which is in line with the low-risk and high-risk token receipt categories, both of which have means around 0.02.

Overall, these statistics highlight the variability and complexity of on-chain transaction behaviors, with a notable concentration in basic send/receive transactions and significantly lower engagement in more specialized or riskier transaction types.

Fig. 1. **Earn Account Deposits and Withdrawals**

This figure illustrates the daily outgoing and incoming values of Earn Accounts for Celsius Networks over a 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.

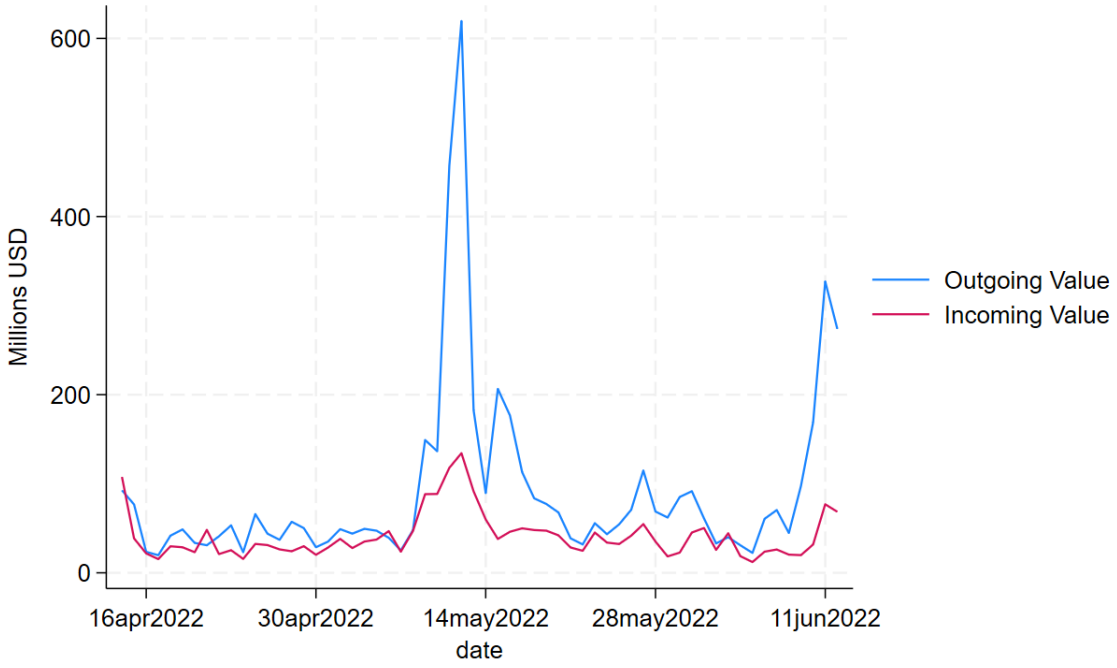


Fig. 2. **Earn Account Initial Holdings**

This chart illustrates the distribution of initial holdings in USD across Earn Accounts for Celsius Networks over a 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.

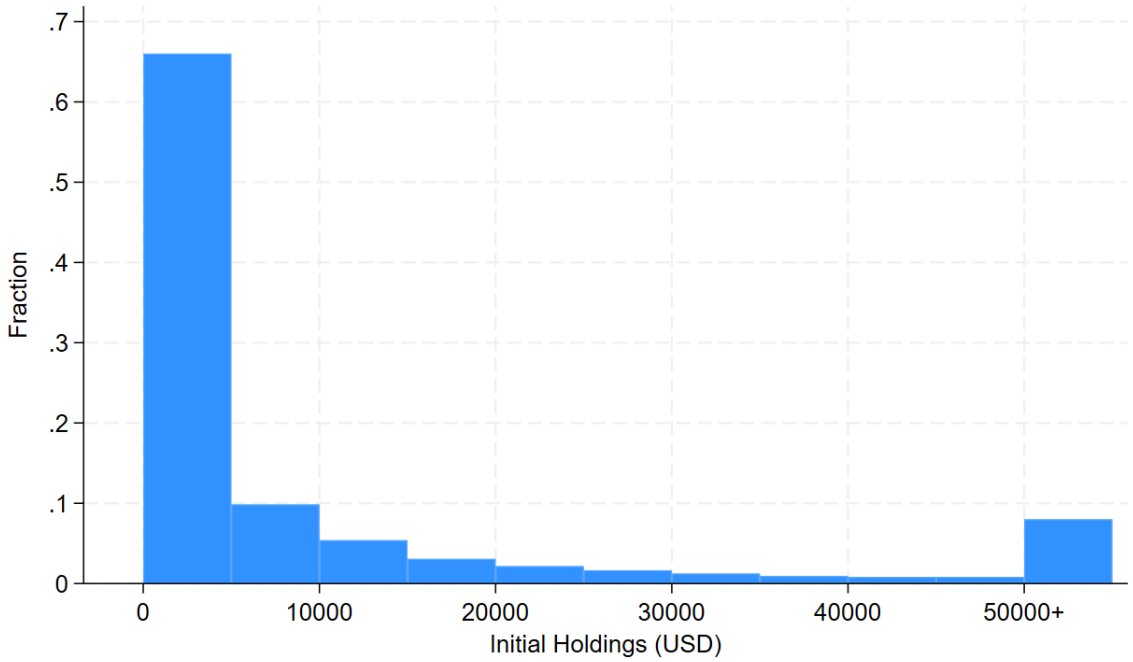


Table 1: **Celsius Depositor Demographics**

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.

Depositor Type %	
Individuals	99.54
Institutions	0.46
Depositor Gender %	
Male	74.53
Female	19.67
Unknown	5.81
Depositor Ethnicity %	
Anglo-Saxon	27.80
German	12.89
Hispanic	9.34
French	8.95
Italian	8.89
Chinese	7.30
Indian	6.15
Russian	4.70
Arabic/Middle Eastern	3.17
African	1.95
Other/Unknown	8.86
N	395,523

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

This table presents the summary statistics for Earn Accounts on the Celsius Network, categorized into three sections: Token Holdings, Transactions, and Balances. Each section provides detailed statistics, including the number of observations (N), mean, standard deviation (SD), and the 25th, 50th (median), and 75th percentiles.

Earn Account Token Holdings	N	Mean	SD	25%	50%	75%
Number of tokens held	395,523	3.61	2.94	2	3	5
Holds BTC indicator	395,523	0.88	0.32	1	1	1
Holds ETH indicator	395,523	0.52	0.50	0	1	1
Holds Stablecoin indicator	395,523	0.13	0.34	0	0	0
Holds Other tokens indicator	395,523	0.67	0.47	0	1	1
Earn Account Transactions	N	Mean	SD	25%	50%	75%
Has incoming transactions indicator	395,523	0.20	0.40	0.00	0.00	0.00
Incoming BTC (USD)	43,546	14,067.69	173,326.70	175.14	895.35	5,372.33
Incoming ETH (USD)	28,285	16,737.71	238,715.60	328.83	1,723.65	6,845.37
Incoing Stablecoin (USD)	19,635	18,137.03	162,850.00	303.19	1,499.84	7,370.30
Incoming Other (USD)	35,330	9,787.902	96,976.91	138.97	524.915	2,920.14
Has outgoing transactions indicator	395,523	0.30	0.46	0.00	0.00	1.00
Outgoing BTC (USD)	73,564	19,438.92	211,399.40	105.31	1,722.85	10,413.08
Outgoing ETH (USD)	48,901	21,587.89	198,360.90	551.50	3,208.33	12,849.42
Outgoing Stablecoin (USD)	38,109	20,884.25	269,914.50	208.03	1,129.20	8,888.00
Outgoing Other (USD)	61,607	10,298.63	171,774.90	148.91	603.80	3323.76
Interest earned	393,544	149.24	1,650.89	0.63	12.78	69.6
Interest earned from BTC (USD)	339,630	50.62	443.60	0.19	3.65	50.00
Interest earned from ETH (USD)	197,688	103.01	1,128.72	0.10	7.43	56.36
Interest earned from Stablecoins (USD)	119,337	131.37	1,385.66	0.01	1.21	19.26
Interest earned from Other (USD)	274,833	84.06	1,458.55	0.06	2.42	17.03
Earn Account Balances (BTC + ETH + USDC)	N	Mean	SD	25%	50%	75%
Initial holdings (USD)	395,523	24,005.57	307,544.60	22.80	900.56	9,260.79
Stranded asset ratio	391,628	0.85	0.32	1.00	1.00	1.00

Table 3: **Stranded Assets and Depositor Demographics**

This table examines the relation between Celsius depositor demographic properties 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 non-zero stranded assets. 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 3.1.1 as explanatory variables. Columns (2) and (4) include user fixed effects 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	-0.035^{***}	-0.023^{***}	-0.027^{***}	-0.019^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Anglo-Saxon indicator	0.002	-0.002	0.000	-0.005^{**}
	(0.002)	(0.002)	(0.002)	(0.002)
German indicator	0.009^{***}	-0.006^{***}	0.005^{**}	-0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Hispanic indicator	0.027^{***}	0.018^{***}	0.024^{***}	0.017^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
French indicator	-0.006^{**}	-0.008^{***}	-0.008^{***}	-0.010^{***}
	(0.002)	(0.002)	(0.003)	(0.002)
Italian indicator	-0.007^{***}	-0.014^{***}	-0.010^{***}	-0.016^{***}
	(0.002)	(0.002)	(0.003)	(0.002)
Chinese indicator	-0.020^{***}	-0.003	-0.015^{***}	-0.002
	(0.003)	(0.002)	(0.003)	(0.003)
Indian indicator	0.026^{***}	0.021^{***}	0.022^{***}	0.018^{***}
	(0.003)	(0.002)	(0.003)	(0.003)
Russian indicator	0.027^{***}	0.024^{***}	0.022^{***}	0.020^{***}
	(-0.003)	(0.003)	(0.003)	(0.003)
Arabic indicator	0.008^{**}	0.001	0.003	-0.003
	(0.003)	(0.003)	(0.004)	(0.003)
African indicator	0.013^{***}	-0.001	0.013^{***}	0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.872^{***}	0.976^{***}	0.888^{***}	0.969^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Controls	No	Yes	No	Yes
Observations	391,628	391,628	395,523	395,523
R-squared	0.004	0.153	0.002	0.092

Table 4: **Stranded Assets and Monitoring Incentives**

This table examines the relation between monitoring incentives and stranded assets. The dependent variables in columns (1) through (4) are the stranded asset ratio, and in columns (5) through (8) are the stranded asset indicator. The independent variables include an institution indicator and the logarithm of 1 plus initial holdings. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Stranded asset ratio				Stranded asset indicator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Institution indicator	-0.127^{***}		-0.060^{***}	-0.043^{***}	-0.106^{***}		-0.055^{***}	-0.043^{***}
	(0.009)		(0.009)	(0.009)	(0.010)		(0.010)	(0.010)
Log(1+initial holdings)		-0.020^{***}	-0.020^{***}	-0.012^{***}		-0.016^{***}	-0.016^{***}	-0.010^{***}
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Constant	0.852^{***}	0.975^{***}	0.975^{***}	0.981^{***}	0.872^{***}	0.967^{***}	0.966^{***}	0.974^{***}
	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)
Additional Controls	No	No	No	Yes	No	No	No	Yes
Observations	391,628	391,628	391,628	391,628	395,523	395,523	395,523	395,523
R-squared	0.001	0.054	0.054	0.170	0.000	0.030	0.030	0.103

Table 5: **Stranded Assets and Wallet Transactions**

This table examines the relation between wallet transactions and the extent of stranded assets after withdrawals were halted at Celsius. The dependent variables include the total number of transactions (column 1), and indicator variables for whether a transaction is categorized as Send/Receive (column 2), DeFi (column 3), NFT (column 4), or Other (Column 5). The variable *post* equals 1 if the week is on or after June 12-18, 2022, which is the date withdrawals were halted. The variable *stranded asset indicator* equals 1 if the user has non-zero stranded assets, which are computed as the amount of initial holdings plus deposits minus withdrawals, in US dollars. The variable of interest is *post* × *stranded asset indicator*. All regressions using ordinary least squares with individual and week fixed effects. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Transaction Types				
	Number of transactions	Send/Receive indicator	DeFi indicator	NFT indicator	Other indicator
	(1)	(2)	(3)	(4)	(5)
Post × Stranded asset indicator	0.070***	0.063***	−0.000	−0.001	0.008
	(0.024)	(0.020)	(0.004)	(0.002)	(0.007)
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	185,185	185,185	185,185	185,185	185,185
R-squared	0.236	0.217	0.171	0.187	0.221

Table 6: **Stranded Assets and Token Transfer Activity**

This table examines the relation between sending and receiving ETH and ERC-20 tokens and the the extent of stranded assets after withdrawals were halted at Celsius. The dependent variables are *send indicator* (columns 1 and 3) and *receive indicator* (columns 2 and 4) for each token based on whether the transaction is categorized as sending or receiving tokens from the wallet. The variable *post* equals 1 if the week is on or after June 12-18, 2022, which is the date withdrawals were halted. The variable *stranded asset indicator* equals 1 if the user has non-zero stranded assets, which are computed as the amount of initial holdings plus deposits minus withdrawals, in US dollars. The variable of interest is *post* × *stranded asset indicator*. All regressions using ordinary least squares with individual and week fixed effects. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	ETH		ERC-20	
	Send indicator	Receive indicator	Send indicator	Receive indicator
	(1)	(2)	(3)	(4)
Post × Stranded asset indicator	0.010^{***}	-0.009^{***}	0.003^{**}	0.004^{**}
	(0.003)	(0.003)	(0.001)	(0.002)
Individual Fixed Effects	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes
Observations	185,185	185,185	185,185	185,185
R-squared	0.197	0.199	0.161	0.190

Table 7: **Stranded Assets and Token Receipt by Risk Level**

This table examines the relation between stranded assets and receiving different types of tokens categorized by riskiness. The dependent variables are indicator variables for whether a wallet received a Stablecoin, a Low-Risk Token, or a High-Risk Token. The variable *post* equals 1 if the week is on or after June 12-18, 2022, which is the date withdrawals were halted. The variable *stranded asset indicator* equals 1 if the user has non-zero stranded assets, which are computed as the amount of initial holdings plus deposits minus withdrawals, in US dollars. The variable of interest is *post* × *stranded asset indicator*. All regressions using ordinary least squares with individual and week fixed effects. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Receive Tokens by Riskiness		
	Receive stablecoin indicator	Receive low-risk token indicator	Receive high-risk token indicator
	(1)	(2)	(3)
Post × Stranded asset indicator	−0.0001	0.0006	0.0041***
	(0.0019)	(0.0019)	(0.0016)
Individual Fixed Effects	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes
Observations	185,185	185,185	185,185
R-squared	0.200	0.199	0.177

Table 8: **Stranded Assets and Wallet Holdings**

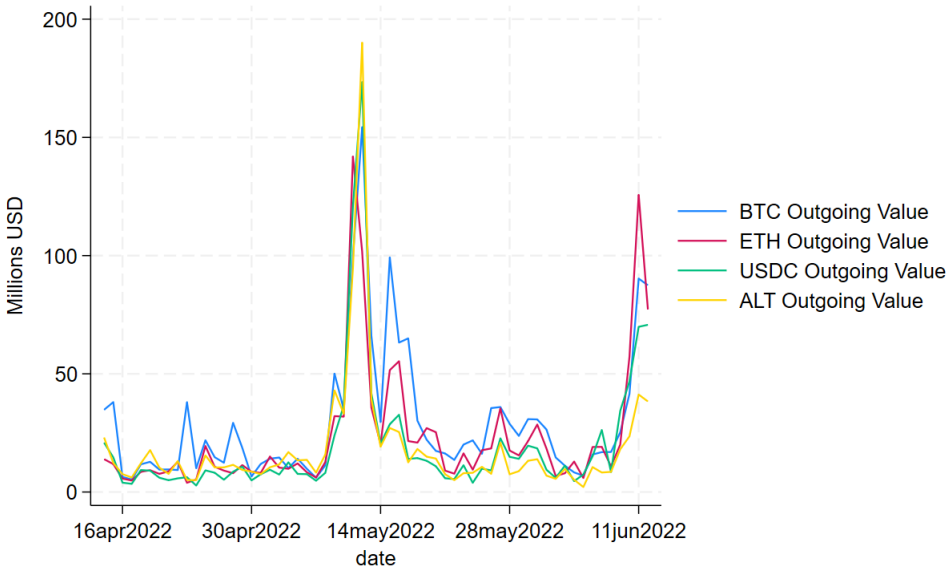
This table examines the relation between wallet characteristics and the extent of stranded assets after withdrawals were halted at Celsius. The dependent variables include the concentration of the wallet where lower values indicate more diversification (column 1), the Moralis-derived risk of the tokens held by the wallet, where lower scores indicate more risk (column 2), our hand-coded measure of risk of the tokens held by the wallet, where lower scores indicate more risk (column 3), wallet returns (column 4), and wallet Sharpe ratio (column 5). 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 non-zero stranded assets, which are computed as the number of initial holdings plus deposits minus withdrawals, in US dollars. The variable of interest is post $\times$ stranded asset indicator. All regressions using ordinary least squares with individual and week fixed effects. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Wallet Characteristics				
	Concentration (HHI)	Moralis risk	Hand-code risk	Daily return	Sharpe ratio
	(1)	(2)	(3)	(4)	(5)
Post $\times$ Stranded asset indicator	$-0.00417 * **$	$0.00924 * **$	$-0.00679 * **$	$0.105 * **$	0.000184
	(0.000758)	(0.000213)	(0.00147)	(0.00127)	(0.00115)
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	9,025,772	8,501,483	6,808,237	8,080,266	8,049,601
R-squared	0.718	0.979	0.195	0.325	0.441

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

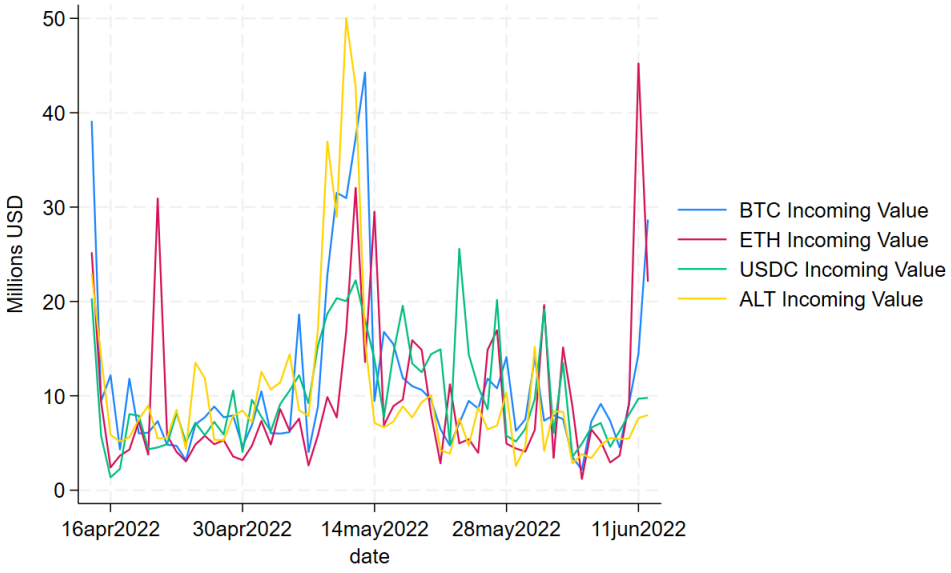


Table A1: **Institution Locations**

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
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 23 specific tokens along with a category for "40 other tokens."

Token	Number of transactions	Transaction value (USD millions)
BTC	773,204	4819.65
ETH	466,290	4207.64
USDC	424,202	3309.16
CEL	214,630	215.76
MATIC	130,856	230.09
ADA	119,510	322.65
DOT	81,213	56.92
USDT	80,536	601.46
LINK	67,799	151.00
SOL	58,312	127.89
LTC	55,847	37.08
SNX	46,010	21.78
XLM	45,887	14.39
AVAX	39,360	41.53
XRP	27,530	48.69
LUNC	26,537	43.35
MCDAI	25,975	30.75
AAVE	23,832	15.24
BNB	23,311	33.27
BCH	22,033	20.69
40 other tokens	252,421	715.68

Table A3: **Detailed Celsius Transaction Types**

This table presents summary statistics on transactions across different account types on the Celsius Netework. The statistics are categorized into three account types: Custody, Earn, and Earn - Interest accounts. We present the number of transactions and the transaction value in millions of USD.

	Number of Transactions	Transaction Value (USD millions)
Account Types		
Custody	529,054	6,166.99
Earn	929,770	8,504.22
Earn - Interest	1,506,639	80.91
Transactions - Custody Accounts		
Incoming		
Internal Account Transfer	147,484	2,143.34
Deposit	89,030	744.39
Swap In	44,392	124.72
Collateral	4,719	176.05
Outgoing		
Withdrawal	119,133	1,780.24
Swap Out	44,392	124.72
Internal Account Transfer	20,843	461.08
Collateral	12,005	401.43
Loan Principal Payment	9,567	122.81
Transactions - Earn Accounts		
Incoming		
Deposit	198,004	1,181.29
Swap In	80,333	153.47
Collateral	39,717	959.15
Internal Account Transfer	20,848	461.02
Outgoing		
Withdrawal	204,718	2,572.29
Internal Account Transfer	164,732	2,301.16
Swap Out	80,333	153.47
Collateral	16,610	254.64
Loan Principal Liquidation	16,305	306.15
Loan Principal Payment	12,853	112.74
Transactions - Earn Interest Accounts		
Incoming		
Interest and Rewards	1,506,639	80.91

Table A4: **Demographics and Token Holdings**

This table examines the relation between demographic characteristics and various aspects of Celsius user cryptocurrency holdings and usage. The dependent variables are the logarithm of the number of tokens held (column 1) and the likelihood of using specific types of cryptocurrencies, including BTC (column 2), ETH (column 3), stablecoins (column 4), and ALT coins (column 5). All regressions using ordinary least squares. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Log(Number of Tokens)	Use BTC	Use ETH	Use Stable	Use Alt
	(1)	(2)	(3)	(4)	(5)
Male indicator	0.590^{***}	-0.012^{***}	0.081^{***}	0.025^{***}	0.084^{***}
	(0.010)	(0.001)	(0.002)	(0.001)	(0.002)
Anglo-Saxon indicator	0.453^{***}	-0.009^{***}	0.091^{***}	-0.017^{***}	0.012^{***}
	(0.018)	(0.002)	(0.003)	(0.002)	(0.003)
German indicator	-0.288^{***}	0.021^{***}	-0.059^{***}	-0.029^{***}	-0.087^{***}
	(0.019)	(0.002)	(0.003)	(0.002)	(0.003)
Hispanic indicator	-0.065^{***}	0.004^{*}	-0.028^{***}	-0.020^{***}	-0.018^{***}
	(0.021)	(0.002)	(0.004)	(0.003)	(0.004)
French indicator	0.096^{***}	-0.023^{***}	0.023^{***}	-0.011^{***}	0.024^{***}
	(0.021)	(0.003)	(0.004)	(0.003)	(0.004)
Italian indicator	-0.183^{***}	0.012^{***}	-0.070^{***}	-0.016^{***}	0.003
	(0.020)	(0.002)	(0.004)	(0.003)	(0.004)
Chinese indicator	0.200^{***}	0.027^{***}	0.029^{***}	0.041^{***}	0.029^{***}
	(0.021)	(0.002)	(0.004)	(0.003)	(0.004)
Indian indicator	0.146^{***}	-0.010^{***}	0.013^{***}	-0.012^{***}	0.011^{***}
	(0.024)	(0.003)	(0.004)	(0.003)	(0.004)
Russian indicator	-0.297^{***}	-0.005	-0.049^{***}	-0.003	-0.031^{***}
	(0.024)	(0.003)	(0.005)	(0.003)	(0.004)
Arabic indicator	0.050^{*}	-0.027^{***}	0.025^{***}	-0.023^{***}	0.012^{**}
	(0.029)	(0.004)	(0.005)	(0.003)	(0.005)
African indicator	-0.101^{***}	-0.041^{***}	-0.015^{**}	-0.031^{***}	-0.030^{***}
	(0.035)	(0.004)	(0.006)	(0.004)	(0.006)
Constant	3.082^{***}	0.890^{***}	0.446^{***}	0.126^{***}	0.610^{***}
	(0.016)	(0.002)	(0.003)	(0.002)	(0.003)
Observations	395,523	395,523	395,523	395,523	395,523
R-squared	0.017	0.003	0.019	0.003	0.011

Table A5: **Monitoring Incentives and Stranded Assets by Account Size**

This table examines the relation between monitoring incentives and stranded assets by account size. Specifically, the analysis is conducted for accounts with initial holdings greater than $1,000 USD (columns 1 and 2) and greater than $10,000 USD (columns 3 and 4). The dependent variables are the stranded asset ratio (columns 1 and 3) and the likelihood of being a Bagholder (columns 2 and 4).

	Initial Holdings > $1,000 USD		Initial Holdings > $10,000 USD	
	Stranded asset ratio	Stranded asset indicator	Stranded asset ratio	Stranded asset indicator
	(1)	(2)	(3)	(4)
Institution	-0.061^{***}	-0.067^{***}	-0.032^{**}	-0.042^{***}
	(0.011)	(0.012)	(0.013)	(0.014)
Log(1+ Initial Holdings)	-0.011^{***}	-0.004^{***}	-0.009^{***}	-0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.949^{***}	0.873^{***}	0.957^{***}	0.895^{***}
	(0.008)	(0.009)	(0.016)	(0.018)
Controls	Yes	Yes	Yes	Yes
Observations	194,032	194,032	95,472	95,472
R-squared	0.130	0.073	0.137	0.077

Table A6: **Summary Statistics: On-Chain Transactions**

This table provides summary statistics for various on-chain transaction activities. We report the number of observations, the mean value, and the standard deviation (SD) for each type of transaction.

	N	Mean	SD
Number of On-Chain Transactions	185,185	0.5488	1.9418
Send/Receive Transaction Indicator	185,185	0.4672	1.6324
DeFi Transaction Indicator	185,185	0.0284	0.3539
NFT Transaction Indicator	185,185	0.0078	0.1548
Other Transaction Indicator	185,185	0.0453	0.5060
Send ETH Indicator	185,185	0.0945	0.2925
Receive ETH Indicator	185,185	0.0718	0.2582
Send ERC-20 Indicator	185,185	0.0135	0.1152
Receive ERC-20 Indicator	185,185	0.0260	0.1592
Receive Stablecoin Token Indicator	185,185	0.0223	0.1476
Receive Low-Risk Token Indicator	185,185	0.0236	0.1517
Receive High-Risk Token Indicator	185,185	0.0198	0.1393