Shock Propagation in Decentralized Lending Network

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Abstract

We study the propagation of financial shocks in decentralized lending platforms using a novel dataset from the Compound protocol, a prominent DeFi lending application on Ethereum. Unlike traditional interbank networks, Compound exhibits a bipartite structure in which users lend and borrow via liquidity pools governed by smart contracts. We construct daily balance sheets for users and pools from January 2020 to June 2024, model the liability network, and apply the DebtRank algorithm to simulate distress cascades following token-specific price shocks. Our findings show that systemic risk is highly concentrated in a small number of pools, and that the network topology is the most robust predictor of contagion, outperforming standard financial indicators. We further show that the structure of systemic risk varies over time and across asset types, with stablecoin pools exhibiting more concentrated and persistent vulnerabilities than crypto pools. These results underscore the need for continuous, topology-aware risk monitoring in algorithmic credit systems.

2012 ACM Subject Classification

Keywords and phrases decentralized finance; systemic risk; network contagion; DeFi lending; Ethereum; Compound protocol; financial networks; smart contracts; DebtRank; liquidity pools

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1 Introduction

There is a growing recognition that network dependencies can help explain both the size and propagation of macroeconomic and idiosyncratic shocks.[1] To that end, traditional banking networks have been extensively analyzed through network-based approaches [4, 21],[2] leveraging models such as DebtRank to quantify the cascading effects of financial distress within complex financial systems [43, 35]. However, the emergence of decentralized finance (DeFi) lending protocols—with over $50 billion in total value locked (TVL)[3] poised for

[1] See, for example, [3] and [23] for theoretical results on the propagation of systemic and idiosyncratic risk in networks, and [19] and [14] for empirical results from micro-data.
[2] See [25] for a survey.
[3] `https://defillama.com/protocols/lending`

further growth as stablecoins and digital asset ownership expand—introduces new forms of interdependencies that warrant further study. Unlike traditional financial institutions, DeFi platforms operate through algorithmic governance and smart contracts, allowing users to lend and borrow assets without centralized oversight. The primary contribution of this paper is to study the propagation of financial shocks and measure systemic risk in the DeFi market, drawing on variation from the Compound Protocol as a case study.

DeFi offers a different financial ecosystem by allowing permissionless access, eliminating reliance on trusted third parties, and enabling composability between financial applications [7]. These features create a more flexible and accessible financial system, but they also introduce new risks, including smart contract exploits, flash loan attacks, and governance challenges. Theoretically, the decentralized nature of the blockchain should mitigate the presence of systemic risk. If many different users all behave independently and according to their own incentives, then idiosyncratic shocks could be muted, and the overall implications for systemic risk are minimal. However, the same features that enable innovation—open access, transparency, and composability—also expand the system's attack surface, making DeFi protocols vulnerable to exploits that can trigger sudden liquidity crises or feedback loops [15].

We study the Compound Protocol [34], which totalled ≈$400 million in market capitalization as of June 2025[4]. In Compound's financial network, liquidity pools serve as intermediaries between lenders and borrowers, creating a bipartite structure that differs from conventional interbank networks. The absence of traditional regulatory safeguards and the automated nature of liquidations introduce novel risk dynamics that require adaptation of existing systemic risk models. We develop a network-based framework that captures the recursive propagation of financial stress in the Compound Protocol and analyze how different topological and financial features influence systemic stability. Using a dataset of transactions within Compound, we compute systemic impact and vulnerability metrics for both liquidity pools and users. We identify key topological and financial drivers of risk and compare our findings to traditional financial networks.

Our results indicate that systemic risk within Compound is highly concentrated among a small subset of liquidity pools, with the top five pools accounting for over XX% of the total systemic impact. We find that pools with high systemic importance also exhibit high vulnerability, making them critical points of failure in the network. Additionally, we observe that the distribution of risk varies significantly over time, with liquidity shocks leading to abrupt changes in the network topology and risk concentration. By applying DebtRank to the DeFi lending protocol, we demonstrate that risk propagation follows distinct patterns compared to traditional finance, largely due to the automated and transparent nature of liquidations. Our analysis suggests that interventions targeting the most influential pools could significantly mitigate systemic risk, which points to the importance of dynamic risk monitoring in decentralized lending protocols despite their presence on the blockchain.

2 Related Work

There is a large and growing literature on the role of networks in economics and finance. Network dependencies help explain how localized shocks—whether idiosyncratic or sectoral—can propagate and amplify into macroeconomic fluctuations. Theoretically, such propagation

[4] `https://coinmarketcap.com/currencies/compound/` and `https://www.coingecko.com/en/coins/compound`

has been formalized in models of input-output linkages and financial networks [3, 23], showing that both the topology of connections and the concentration of exposures shape systemic outcomes. Empirically, production and financial network data have been used to demonstrate how shocks transmit through supplier–buyer chains [14] and through firm-specific demand shifts [19]. Within the domain of finance, a parallel strand of research has modeled interbank markets as networks, highlighting how the structure of claims and exposures influences both contagion and stability [4, 21]. As summarized in [25], these frameworks have given rise to a variety of contagion metrics, including DebtRank [43, 35], which quantifies how financial distress propagates through layered interdependencies before defaults occur.

Systemic risk in financial networks has also been extensively studied using complex network theory [13, 10], and DebtRank emerging as a prominent tool for assessing the transmission of financial distress [43, 35]. Originally introduced to model interbank contagion, DebtRank quantifies how losses accumulate and spread within a network before defaults occur. The framework has been applied to traditional banking systems, highlighting the role of interconnectedness in amplifying systemic vulnerabilities. Studies have demonstrated that while increased interconnectivity can mitigate idiosyncratic risks, it also heightens systemic fragility by creating contagion pathways if certain groups of users are clustered [12].

The relevance of network models has extended beyond traditional finance, finding applications in DeFi, where lending protocols such as Compound and Aave facilitate algorithmic credit intermediation. Unlike banks, DeFi protocols operate via smart contracts, enforcing collateralized borrowing without centralized oversight [9]. Recent research has examined the unique arbitrage mechanisms within DeFi [18, 28], including miner extractable value (MEV) and the role of block builders, proposers [37], and arbitrageurs in shaping market outcomes [8]. While traditional finance relies on established intermediation chains [26, 20, 29], DeFi introduces a transparent, but fragmented market structure with novel sources of rent extraction [41].

One of the critical distinctions in DeFi lending networks is the role of collateralization (and health factors) in risk transmission. When loans become undercollateralized, the underlying assets can be sold at a discount to repay the outstanding debt by other users. This liquidation mechanism can undermine DeFi protocol stability [44] and poses potential risks to the broader ecosystem [42, 31, 27]. Previous studies have analyzed the impact of collateral requirements on borrower stability and liquidation dynamics [22, 38] in traditional finance. However, the recursive effects of financial distress, particularly when asset prices decline rapidly, are not well understood. Our study bridges this gap by integrating DebtRank with health ratio dynamics to track the progressive diffusion of financial distress in Compound, incorporating insights from blockchain-based intermediation models that analyze how information asymmetry and arbitrage drive financial outcomes in DeFi [16, 32].

Moreover, while prior work has examined systemic risk in interbank networks using eigenvalue-based stability measures [11, 25], their applicability to DeFi lending has been limited. DeFi platforms exhibit unique leverage dynamics, where asset price fluctuations directly affect borrower solvency and liquidation events trigger cascading effects[31]. By incorporating endogenous shock propagation mechanisms, our methodology extends traditional systemic risk measures to decentralized environments, offering a more comprehensive understanding of financial contagion in DeFi lending protocols. Our approach builds on the emerging literature on blockchain financial intermediation by contextualizing risk propagation within the structure of Ethereum's proof-of-stake ecosystem [1, 17].

Finally, our paper builds on literature from spatial econometrics [6, 33]. Although there are well-known problems associated with causal inference [24, 24], our focus lies elsewhere.

Specifically, we use simulated equity losses generated via the DebtRank algorithm to perform a variance decomposition and assess how much of the observed propagation of financial distress across the DeFi network can be attributed to different financial and topological features. Because our outcome variable (the DebtRank score) is derived from a structural simulation rather than directly observed market behavior, the usual concerns around endogeneity or omitted variables are less central. We are not attempting to estimate causal effects from observational price data, but rather to understand which features of the network structure most influence the simulated spread of shocks under assumptions about distress transmission.

3 Methodology

3.1 Balance Sheet Construction

To understand the financial interdependencies within the Compound lending protocol, we construct balance sheets for both users and liquidity pools by drawing an analogy with traditional accounting. In Compound, users supply assets, referred to as *tokens*, into liquidity pools and receive in return *cTokens*, which are interest-bearing tokens representing their supplied assets. These *cTokens* can also be pledged as collateral to borrow assets from the protocol. The financial positions of users and pools are represented in Table 1 through stylized balance sheets.

- **Liabilities**
  - *Pools:* Users' deposits, which the pool owes to lenders.
  - *Users:* Credit lines from pools as outstanding debts, i.e., the borrowed amounts from pools.
- **Assets**
  - *Pools:* Credit lines to users and external assets of the available tokens (i.e., unutilized tokens) stored in the liquidity pool.
  - *Users:* Deposits held in pools, represented by *cTokens*.

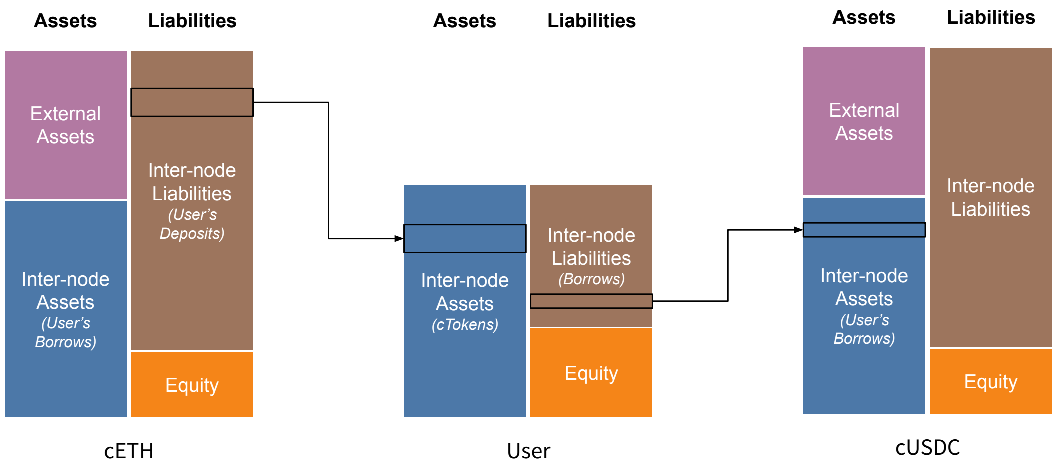


Figure 1 Pools' and users' balance sheets and their inter-node relationships.

Figure 1 presents a schematic view of these financial positions, delineating the asset-liability structure of both users and pools as well as the inter-node exposures that arise from

	User	Pool
Assets		
External assets	$\emptyset$	Tokens
Inter-node assets	Deposits (cTokens)	Lendings (cash + reserves)
Liabilities		
External liabilities	$\emptyset$	$\emptyset$
Inter-node liabilities	Borrows	Deposits
Equity	Deposits - Borrows	Tokens + Lendings - Deposits

Table 1 Balance sheet structure of the user and the lending pool.

lending and borrowing activity. Users hold inter-node assets in the form of cTokens and incur inter-node liabilities through their borrowings. Liquidity pools, in contrast, hold a combination of tokens and loans (originated through user borrowing) on the asset side, and carry user deposits as inter-node liabilities. This balance sheet representation abstracts from off-protocol positions—such as users' external holdings of fiat or crypto assets not supplied to Compound—allowing us to isolate and focus on endogenous financial linkages within the system. Incorporating such exogenous assets and their role in risk absorption or amplification is an important direction for future research.

3.2 Financial Network Representation

Using the asset-liability relationships defined above, we represent the Compound protocol as a directed bipartite network, where nodes consist of liquidity pools $\mathcal{P} = 1, ..., p$ and users $\mathcal{U} = p + 1, ..., p + u$. An edge of weight L_{ij} denotes a liability of node i to node j—that is, node i owes to node j. Due to the bipartite nature of the network, the liability matrix L satisfies $L_{ij} = 0$ for all $i, j \in \mathcal{U}$ or $i, j \in \mathcal{P}$—that is, liabilities only exist between users and pools, and not within the same group.

Figure 2 provides an illustrative example of the bipartite financial network generated by the Compound lending protocol, in which users and lending pools form two disjoint sets of nodes. Directed edges represent financial exposures, with arrows pointing from creditors to debtors—that is, from lenders to borrowers. Each node is associated with a stylized balance sheet decomposing assets, liabilities, and equity, but for expositional clarity, node sizes are not drawn to scale. The structure highlights the dual role users can play in the system: some users act as pure lenders (e.g., the second user from the left), supplying assets to lending pools without initiating any borrowings, while others both supply and borrow. This intermediation is facilitated by the pools, which aggregate deposits and extend credit to users against collateral. On the pools' balance sheets, deposits appear as liabilities, while outstanding loans (termed "credit lines") appear as inter-node assets. For users, the mirror image holds: cToken deposits are assets, and borrowings are inter-node liabilities. By representing users and pools as distinct but financially interlinked agents, this bipartite structure captures the systemic exposure patterns that arise endogenously from decentralized financial activity. It forms the foundation for analyzing shock transmission and contagion dynamics in the protocol.

From this network, we derive key financial metrics to evaluate the positions and risks of nodes within the protocol.

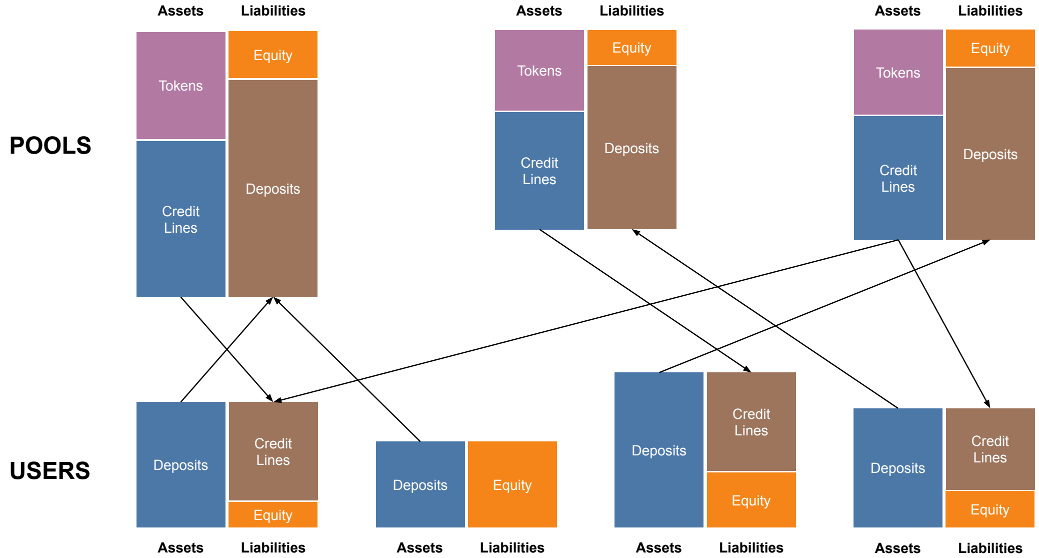


Figure 2 Bipartite network of Compound. Arrows point to debtors. The second user is a pure lender. Node sizes are not proportional to balance sheet sizes.

- **Equity:** The equity E_i of node i represents its equity position and is calculated as:

$$E_i = \tilde{X}_i + \sum_{j \in \mathcal{N}} L_{ji} - \sum_{j \in \mathcal{N}} L_{ij}, \tag{1}$$

where $\tilde{X}_i$ denotes the external assets of node i. For users ($i \in \mathcal{U}$), we assume $X_i = 0$ as external assets are excluded. We also assume that all liabilities are internal to the protocol.

- **Health Ratio:** The health ratio is a lending protocol-specific measure used to assess the solvency of users and their liquidation risk. For each user $i \in \mathcal{U}$, the health ratio H_i is given by:

$$H_i = \frac{\sum_{j \in \mathcal{P}} c_j L_{ji}}{\sum_{j \in \mathcal{P}} L_{ij}}, \tag{2}$$

where L_{ji} denotes the liability of pool j to user i (i.e., the supplied amount), and L_{ij} denotes the liability of user i to pool j (i.e., the borrowed amount). The collateral factor $c_j \in (0, 1]$ reflects the proportion of the deposited assets in pool j that can be borrowed against, which is determined by the protocol. A health ratio below 1 implies a risk of liquidation.

- **Utilization Ratio:** For each liquidity pool $i \in \mathcal{P}$, the utilization ratio U_i measures how much of the supplied liquidity is currently borrowed:

$$U_i = \frac{\sum_{j \in \mathcal{U}} L_{ji}}{\sum_{j \in \mathcal{U}} L_{ij}}, \tag{3}$$

where L_{ji} captures the total borrowings from pool i by users j, and L_{ij} captures the supply deposited into the pool i. This metric reflects the pool's capital efficiency. Notably, for users, this ratio is the inverse of the health ratio but does not incorporate collateral factors.

- **Self-borrowing:** In the Compound protocol, it is possible for users to simultaneously supply assets to a pool and borrow from the same pool. This behavior, known as *self-borrowing*, is commonly employed as a liquidity mining strategy. Users engage in such activity to maximize their rewards in the form of COMP, the protocol's governance token, which can be either sold on secondary markets or used to participate in protocol governance. We define the **self-borrowing ratio** of a node $i \in \mathcal{N}$ (whether a user or a pool) as:

$$S_i = \frac{\sum_{j\in\mathcal{N}} \min\left(L_{ij}, L_{ji}\right)}{\sum_{j\in\mathcal{N}} L_{ij}}, \tag{4}$$

  where L_{ij} denotes the amount that node i borrows from node j, while $min(L_{ij}, L_{ji})$ represents the self-borrowing amount in the node j. A high ratio indicates that a large portion of the borrowing by i is backed by the same supply j.
  - For users $i \in \mathcal{U}$, this captures how much they borrow from pools where they also supply.
  - For pools $i \in \mathcal{P}$, it captures how much of the borrowing they receive is from users who are also supplying to them (i.e., users self-borrowing from that pool).

3.3 DebtRank Algorithm

To analyze systemic risk within the protocol, we simulate the propagation of financial distress through the network using the DebtRank algorithm, originally introduced by Battiston et al. (2012) [43]. Although the protocol forms a bipartite network between users and pools, we treat the union of nodes $\mathcal{N} = \mathcal{P} \cup \mathcal{U}$ as a homogeneous set in the simulation. This is justified by the fact that both user and pool nodes share the same balance sheet structure, and in this work, we assume that the mechanism of distress propagation follows the same rules across them.

We first define an impact matrix $W_{ij} = \min\left\{1, \frac{L_{ij}}{E_j}\right\}$, where W_{ij} quantifies the relative impact of node i's distress on node j. The effect is capped at 1 to ensure that the transmitted loss does not exceed the total equity of the receiving node.

Each node associates one of the following states: undistressed (U), distressed (D), and inactive (I). The states of all nodes are updated in parallel through successive rounds whose order we denote by t. We define the state variable $s_i(t) \in \{U, D, I\}$, and set $s_i(0) = U$ for all $i \in \mathcal{N}$ to ensure that all nodes start in the undistressed state. Equity losses $h_i(t)$ evolve according to:

$$h_i(t+1) = \min\left\{1, h_i(t) + \sum_{j\in\mathcal{D}(t)} W_{ij} h_j(t)\right\}, \tag{5}$$

where $\mathcal{D}(t) = \{i : s_i(t) = D\}$ denotes the set of all nodes in the distressed state at round t of the contagion process.

After updating $h_i(t)$, the state of each nodes is updated for all $t \geq 2$ as follows:

$$s_i(t) = \begin{cases} D & \text{if } s_i(t-1) = U \text{ and } h_i(t) > 0; \\ I & \text{if } s_i(t-1) = D; \\ s_i(t-1) & \text{otherwise.} \end{cases} \tag{6}$$

The state-transition rule mitigates propagation because a node transmits the shock once and becomes inactive afterward. The DebtRank algorithm repeatedly iterates until the procedure has converged (i.e., $s(t) = s(t-1)$) or every node is inactive.

Unlike the recursive DebtRank variant introduced in a later extension of the model [35], our implementation avoids infinite reverberations by excluding feedback loops (cyclic back-propagation), i.e., paths that revisit the same edge, making the algorithm more suitable for networks with densely connected components.

The final DebtRank score, denoted by R, measures the total economic impact of distress propagation beyond the initial shock. Following the original DebtRank paper [43], we compute the measure as:

$$R = \sum_{i \in \mathcal{N}} h_i(T) v_i - \sum_{i \in \mathcal{N}} h_i(1) v_i, \tag{7}$$

where $v_i = \sum_j L_{ji} / \sum_k \sum_l L_{kl}$ is the relative economic value of node i, $h_i(1)$ is the post-shock initial distress, and $h_i(T)$ is the final distress level at convergence. The DebtRank score R thus reflects the marginal systemic impact caused by the contagion process, accounting for both direct and indirect transmissions of distress through the network.

3.3.1 Price Shock Initialization

To initiate the contagion process, we simulate an exogenous price shock that impacts a specific token k, causing a subset of nodes to transition from the *undistressed* state (U) to the *distressed* state (D). This mechanism serves as the trigger for the DebtRank dynamics.

We model the shock as a proportional price drop of $\varepsilon \in (0, 1]$ in token $k \in \mathcal{P}$ at time $t = 1$. This devaluation affects all assets and liabilities denominated in token k, including both user positions and pool exposures. The entries in the liability matrix L are adjusted accordingly:

$$L_{kj}(1) = L_{kj}(0) \times (1 - \varepsilon), \tag{8}$$

$$L_{jk}(1) = L_{jk}(0) \times (1 - \varepsilon), \quad \text{for all } j \neq k. \tag{9}$$

The external asset vector $\tilde{X}$ is also updated as:

$$\tilde{X}_k(1) = \tilde{X}_k(0) \times (1 - \varepsilon). \tag{10}$$

These updates yield a modified liability matrix $L(1)$ and external asset vector $\tilde{X}(1)$, which are then used to compute the post-shock equity $E_i(1)$ for each node. The initial distress level $h_i(1) \in [0, 1]$ is then determined by comparing the post-shock equity $E_i(1)$ with the pre-shock equity $E_i(0)$, following the standard DebtRank initialization procedure.

Note: At this stage, we define all variables relative to their post-shock values—i.e., liabilities $L(1)$, equity $E(1)$, and distress $h(1)$—-which serve as the inputs for the following propagation process.

The rationale for rescaling both assets and liabilities lies in the structure of DeFi protocols. Unlike traditional financial systems, where liabilities are denominated in fiat terms (i.e., US dollar), DeFi liabilities are typically recorded in token units. As a result, a token price drop simultaneously reduces both the value of the supplied collateral and the value of the borrowed liabilities, necessitating an update on both sides of the balance sheet.

Following the price shock, we compute the initial equity loss for each user $i \in \mathcal{U}$ as:

$$h_i(1) = \frac{E_i(0) - E_i(1)}{E_i(0)}. \tag{11}$$

Users experiencing any non-zero equity loss ($h_i(1) > 0$) are transitioned to the distressed state (D) based on the state transition rule defined in Equation (6). Notably, $h_i(1)$ may take negative values when users benefit from the shock, particularly in cases where the price of the asset they have borrowed decreases. In such scenarios, the reduction in liability results in an improvement in the user's net equity. Our framework accommodates this possibility by allowing $h_i(1) < 0$, though such users are not marked as distressed and retain some buffer to absorb future shocks.

3.4 Regression Specification

We aim to uncover the role of financial and topological variables as determinants of systemic risk in lending protocols. The first goal is to assess the impact of the network topology on the DebtRank in the price shock scenario.

To do so, we simulate the daily DebtRank of lending pools, generating a series of network snapshots over time. We then apply machine learning techniques to identify the topological features of the global network that best explain variations in DebtRank. This approach takes advantage of the uniqueness of our dataset, which includes high-frequency snapshots—something rarely available in traditional finance (TradFi), where data collection occurs at much lower frequency.

For interpretability, our baseline specification builds on the linear model of social interactions originally proposed in [36]:

$$Y_{i,t} = \alpha + \beta \mathbf{X}_{i,t} + \gamma \sum_{j=1}^{N} \mathbf{W}_{ij,t} \mathbf{X}_{j,t} + \lambda \sum_{j=1}^{N} \mathbf{W}_{ji,t} \mathbf{X}_{j,t} + \varepsilon_{i,t}. \tag{12}$$

where $Y_{i,t}$ denotes the DebtRank score of pool i at time t,[5] $\mathbf{X}_{i,t}$ denotes the characteristics of the pool, and $\mathbf{X}_{j,t}$ denotes the characteristics of users. Weighting the users' characteristics by the liability matrix $\mathbf{W}_{ij,t}$ ensures that we are selecting the borrowers associated with pool i. Therefore, γ captures the impact of borrowers' characteristics, weighted by the relative size of their loans, on the DebtRank score of pool i. Conversely, λ captures the impact of lenders' characteristics on the DebtRank score of pool i.

The characteristics of the pools include not only financial variables (e.g., equity as a percentage of liabilities, asset size, and utilization ratio) but also topological variables (e.g., centrality). For users' characteristics, we use the same set of covariates as for the pools. We treat each snapshot as an independent observation. Although user behaviors and network structures evolve over time, each snapshot represents a distinct, self-contained network that reflects user positions and interactions at the end of a given day. Since our goal is to analyze how network structure and financial variables at a specific point in time influence systemic risk, treating snapshots as independent is consistent with the cross-sectional nature of our analysis.

This specification is borrowed from the spatial econometrics literature, where linear-in-means models are used to account for interdependencies across units (see [2] for a recent survey). In our context, the network of liabilities serves as a non-geographic analogue to spatial proximity, with the weights in the liability matrices $\mathbf{W}_{ij,t}$ capturing financial proximity. However, unlike many spatial applications, we avoid the so-called "reflection

[5] We only use one size for the price shock and keep it constant over time.

problem" emphasized by [36], because DebtRank is simulated independently for each pool. That is, there is no simultaneity in the outcome variable across nodes: The DebtRank of pool i does not contemporaneously depend on the DebtRank of other pools, which allows for a clean identification of peer effects via borrowers' and lenders' characteristics.

Formally, our model corresponds to a Spatial Lag of X (SLX) model, where spatial dependence arises exclusively through the independent variables of neighboring units (see [2]). While the SLX model is well established in spatial econometrics, its use in this context is original: we apply it to model the propagation of systemic risk in decentralized lending markets via network-based exposure. By leveraging high-frequency, structured snapshots of financial positions, we offer a novel application of the SLX framework to assess how characteristics of connected agents contribute to the vulnerability of each pool within the lending protocol.

4 Descriptive Analysis

4.1 Data Description

Our analysis relies on daily snapshots of the Compound V2 protocol collected between January 1, 2020, and June 15, 2024. The data is sourced from The Graph,[6], which provides an indexed subgraph of the Compound V2 smart contracts. After June 2024, this hosted subgraph was deprecated following The Graph's migration to a decentralized network.[7] However, by that time, Compound V2 was effectively deprecated as well, with almost negligible user activity remaining.

Each daily snapshot is taken at the final block of the day in Coordinated Universal Time (UTC) and contains comprehensive information on both lending pool characteristics and user positions:

- **Lending pool characteristics:** For each lending pool, we collect snapshot data on total deposits, total borrows, available liquidity (cash), reserves, and collateral factor. The pool's external assets are defined as the sum of cash and reserves, as shown in Table 1.
- **Price oracles:** Compound uses the token price data from Chainlink's decentralized price oracles, which serve as the protocol's source of truth for calculating asset valuations.[8] We collect the token price in U.S. dollars as reported at the final block of each day.
- **User positions:** For each user, we record their deposit and borrow positions across supported assets, i.e., the amount each user lent and borrowed from each lending pool. These values are normalized in U.S. dollars using daily token prices to construct the liability matrix L_{ij} as defined in Subsection 3.2.

This granular dataset allows us to reconstruct the balance sheets of lending pools and users, as well as the evolving liability network, enabling the analysis of systemic risk propagation under various price shock scenarios.

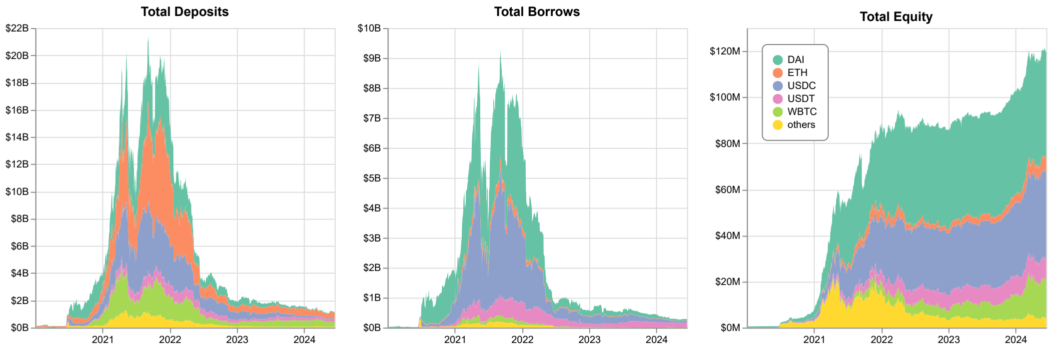


Figure 3 Evolution of deposit and borrow amounts of the top lending pools in Compound V2

4.2 Descriptive Statistics

We examine the evolution of Compound V2 using the aggregate lending and borrowing positions of users, as shown in Figure 3. The protocol experienced its peak activity in 2021, followed by a gradual decline in usage over subsequent years. The figures on the left and middle panels reveal persistent user preferences, with ETH and USDC consistently serving as the dominant supplied assets, while borrowing activity remained primarily concentrated in USDC and DAI. On the right panel, the total net worth of the protocol increased over time, reflecting the accumulation of profits retained in the pool reserves.

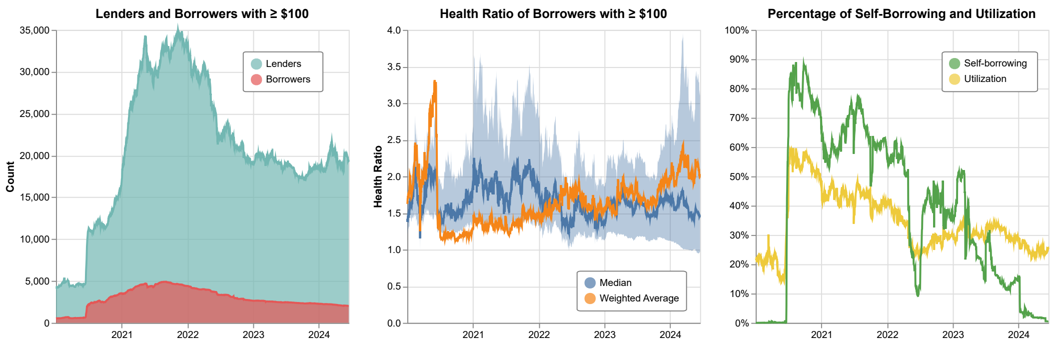


Figure 4 Evolution of lenders and borrowers, health ratio, and the percentage of self-borrowing activities and utilization

Figure 4 illustrates the evolution of user behavior in Compound V2, capturing trends in the number of active users, health ratios, self-borrowing prevalence, and utilization ratios over time. To focus on economically significant users, we consider only lenders and borrowers with positions exceeding 100 USD. The number of active participants grew steadily from early 2020, reaching a peak of approximately 35,000 lenders and nearly 5,000 borrowers by the end of 2021. Both figures declined sharply beginning in mid-2022 and stabilized after 2023, albeit at much lower levels of total value locked.

[6] The Graph: `https://thegraph.com/`
[7] See: `https://thegraph.com/blog/sunrise-here-the-graph-network/` and `https://thegraph.com/docs/en/archived/sunrise/`
[8] Compound v2 Price Feed: `https://docs.compound.finance/v2/prices/`
Chainlink Data Feeds: `https://data.chain.link/feeds`

The sharp increase in borrowing activity coincides with the launch of the COMP incentive program in June 2020, which distributed rewards to users engaged in borrowing [40]. This led to a sudden surge in both self-borrowing and the utilization ratio. However, as the level of incentives declined, self-borrowing dropped to nearly zero, and the utilization ratio stabilized between 20% and 30% from 2022 onward.

The right panel of the figure displays the median and weighted average of the health ratio of borrowers, along with interquartile bands. Following the introduction of the incentive program, the median health ratio hovered around 1.5, suggesting that users maintained their positions near the liquidation threshold. The weighted average health ratio was even lower than the median during 2021 and 2022, implying that large borrowers were more aggressively optimizing their leverage positions. As self-borrowing diminished after 2022, the weighted average health ratio increased, reflecting the exit of large, highly leveraged participants from the protocol.

4.2.1 Impact of Price Shocks

We simulate exogenous price shocks on the Compound V2 liability network by applying shocks of varying magnitudes (from 10% to 50%) to five major lending pools: DAI, ETH, USDC, USDT, and WBTC. For each of these pools, we compute the DebtRank score over time under different shock scenarios. The results are presented in Figure 5.

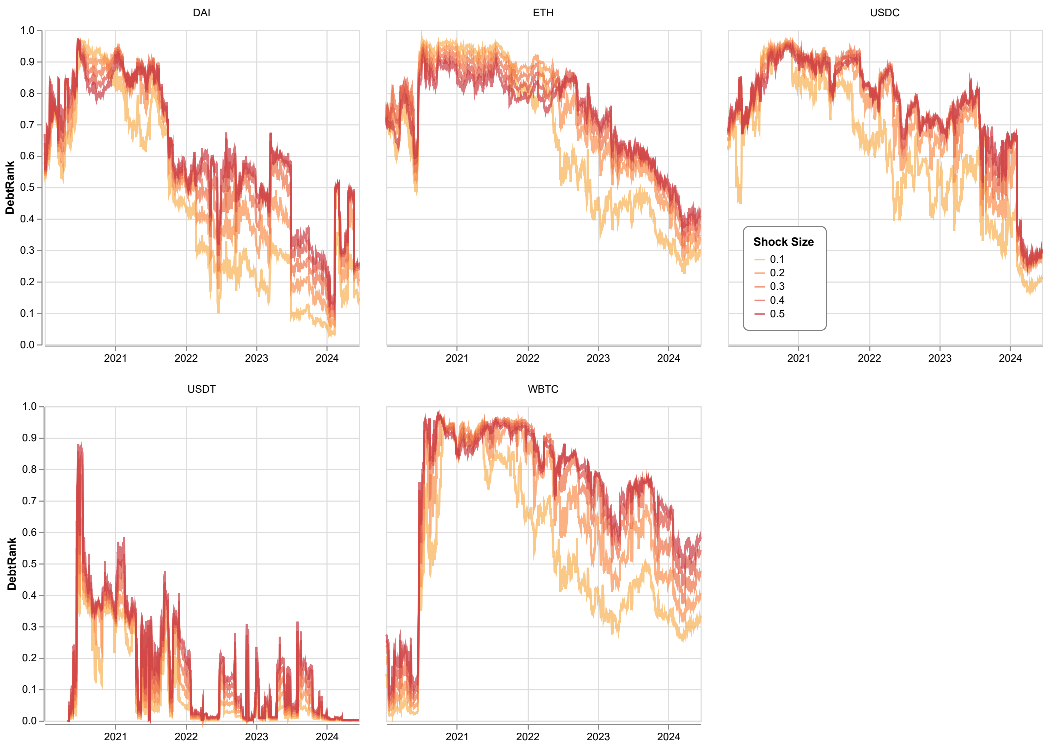


Figure 5 DebtRank scores following price shocks to the five major assets in Compound V2, under varying shock sizes from 10% to 50%.

We observe that the DebtRank scores for most pools, especially DAI, ETH, USDC, and WBTC, were extremely high, often approaching 1, during the early phase of the protocol until its peak in 2020–2021. This indicates a near-complete contagion scenario where distress propagates to the entire system. While this represents a worst-case scenario, it aligns with the assumptions of the DebtRank algorithm, which models distress propagation as being proportional to the loss of equity following a distress. Moreover, given the hub-and-spoke structure of this financial network, where lending pools act as hubs connecting users through credit relationships, the resulting contagion tends to spread broadly, affecting the entire system.

The USDT pool stands out as an exception, as it was disabled as a collateral asset—that is, its collateral factor is 0. Nonetheless, the pool still has non-zero DebtRank values from users who deposit USDT to the protocol while borrowing other assets using different collateral, allowing distress to propagate through indirect exposure.

Over time, DebtRank scores gradually declined, particularly after 2022. This trend suggests an increasing robustness of the protocol's structure or reduced systemic exposure. As expected, the intensity of contagion is positively correlated with the size of the shock, where larger price shocks produce higher DebtRank scores. In most cases, the shock devalues users' collateral, thereby triggering the propagation of distress through the collateral channel.

In certain cases, we observe a reversal in the trend of DebtRank scores—notably for DAI in late 2020 and ETH from mid-2020 to mid-2022. These periods coincide with elevated levels of self-borrowing activity. When a shock primarily affects the valuation of nodes engaged in self-borrowing, the overall systemic effect, as measured by R, may appear lower despite the substantial size of the initial shock. This is because the distress does not propagate widely through the network, and the impact on each node, denoted by h, is capped at 1 in the DebtRank formulation.

4.2.2 Shock Amplification

While the Impact of the Price Shocks section quantifies the extent of distress propagation using DebtRank scores, here we focus on the amplification properties of Compound's network structure—how localized shocks to individual assets generate disproportionately large systemic effects depending on their position in the network and prevailing balance sheet configurations.

The amplification dynamics differ markedly across assets and over time in Figure 5. For DAI, ETH, USDC, and WBTC, even moderate shocks (20–30%) during 2020–2021 produce system-wide DebtRank scores exceeding 0.8, implying that a localized devaluation of collateral can trigger extensive second-round effects across the protocol. This amplification is a function of both network topology and user leverage: highly connected pools and overcollateralized positions amplify the effective transmission of distress beyond the directly affected nodes. Notably, this amplification is nonlinear in shock size. For instance, the difference between a 30% and a 50% shock often results in a much larger increase in systemic distress, rather than a proportional one. This is especially visible in the WBTC and USDC panels, where higher-magnitude shocks rapidly push DebtRank scores toward 1. These inflection points highlight thresholds beyond which the protocol's internal buffers, such as collateral margins and liquidation mechanisms, become insufficient to contain contagion.

Amplification effects also vary temporally. The declining sensitivity to shocks after 2022 suggests that either users reduced leverage ratios, pools tightened collateral requirements, or riskier forms of engagement (e.g., recursive borrowing) became less common. However, the persistence of amplification in certain assets, such as DAI and WBTC, indicates that specific market structures or behavioral patterns (e.g., circular borrowing, concentration of collateral types) continue to pose latent risks even under more stable conditions.

5 Econometric Analysis

5.1 Features Extraction

We construct a panel dataset that integrates pool-level financial indicators, detailed topological network metrics, and user-aggregated attributes for DeFi lending pools on a daily basis. The primary outcome variable is the DebtRank score, calculated under exogenous token price shocks of 10%, 20%, 30%, 40%, and 50%. These shocks are applied separately to each of the five largest liquidity pools by market size—ETH, WBTC, DAI, USDC, and USDT—to simulate system-wide stress originating from critical assets.

To identify the key determinants of systemic risk, we assemble a comprehensive set of explanatory variables that reflect both financial characteristics and structural properties of the Compound's decentralized lending network.[9]

- **Network-level features** include the number of depositors and borrowers, the total amount of lending and borrowing (normalized in U.S. dollars), overall utilization ratio, and percentage of self-borrow across all lending pools. We also calculate network topology metrics such as network density and reciprocity.
- **Shocked pool features** include total deposits, total borrows, utilization ratio, external assets, and equity, both in absolute terms and as percentage shares relative to the system-wide totals. In addition, classical network centrality measures, i.e., PageRank, hub and authority scores, and closeness centrality, are used to quantify the structural importance of the shocked pool within the lending network.
- **User features** capture the behavior and exposures of users interacting with the shocked pool. These include in- and out-degrees for lenders and borrowers, total equity, health ratios, percentage of self-borrowing, and health ratios. To account for distributional effects, we also compute Herfindahl indices for deposit and borrowing weights. All metrics are calculated as weighted averages across users to summarize aggregate behavioral patterns.

These features are subsequently used in a sequence of OLS regressions with Lasso-based feature selection. We aim to investigate whether the size and distribution of the shocked pool and users, as well as their diversity and interconnectedness, influence the propagation of systemic risk in each shock scenario.

5.2 Structural Break

After merging all features by date and asset, we rigorously preprocess the data: duplicate, constant, and perfectly collinear columns are removed, and all predictors are standardized. To mitigate multicollinearity, we compute the *Variance Inflation Factor (VIF)* for each feature and retain only those with VIF ≤ 10. Note that this entire procedure is applied separately for each shock size, ensuring that the feature selection and preprocessing are tailored to the specific characteristics of each shock scenario.

To identify potential regime shifts in the determinants of systemic risk, we implement a *rolling Chow test (F-statistic)* to detect structural breaks in the linear relationship between the DebtRank score and the full set of standardized predictors. For each possible break point, the test computes an F-statistic, and the date with the highest value is reported as the candidate break date. For the 10% shock, the maximum F-statistic is 522.82, corresponding

[9] See Appendix A for a detailed description of the features used in the analysis.

to the 2021-08-07 snapshot. However, the rolling Chow test always identifies a date with the highest F-statistic, regardless of statistical significance. Statistical significance is assessed by comparing the maximum F-statistic to the critical value at the chosen significance level (here, 5%), which depends on the number of model parameters and the sample sizes before and after the candidate break. In our case, the high F-statistic indicates a statistically significant structural break, reflecting a major shift in the system's dynamics or the influence of these variables on systemic risk propagation.

Accordingly, our subsequent analysis focuses exclusively on the post-break period, as this segment is characterized by a more stable and homogeneous regime. Restricting attention to post-break data ensures that the estimated relationships are not confounded by structural changes and better reflect the prevailing determinants of systemic risk in the current environment.

5.3 Lasso Regression

We apply a *Lasso regression* with cross-validation to identify the most relevant predictors of the DebtRank score. Only features with non-zero coefficients were retained, ensuring that the models remain interpretable and robust against overfitting. This approach consistently selected a core set of variables across all asset groups, underscoring their importance in explaining systemic risk.

We then estimate a sequence of *OLS regressions* using the Lasso-selected features for a 10% shock scenario, as reported in Table **??**.[10] Each column in the table represents a progressively richer model: column (1) includes only the most basic topological features, column (2) adds additional network metrics, and column (3) incorporates all selected features, including financial variables. In column (4), we further include pool dummies (with DAI as the reference category) to control for unobserved heterogeneity across pools.

The results highlight the dominant role of topological features in explaining DebtRank shocks. Notably, the model with only topological features already achieves a substantial R^2 of 0.58, capturing about 69% of the variance explained by the full model ($R^2 = 0.84$). Adding further topological features in column (2) yields a moderate improvement ($R^2 = 0.68$), while the inclusion of financial variables in column (3) provides additional but comparatively minor gains in explanatory power. A formal F-test confirms that the improvement in model fit from adding financial features is statistically significant (p-value < 0.05), but the base explanatory power comes from the topological structure. Among the topological features, *lenders' out-degree (wavg)* stands out as the single most influential predictor. Its inclusion alone explains a significant portion of the variance in DebtRank, as confirmed by both the R^2 statistics and feature importance analyses. Overall, these findings indicate that the network structure—and especially the connectivity of lenders as captured by *lenders' out-degree (wavg)*—is a primary determinant of systemic vulnerability, even before accounting for traditional financial characteristics.

In column (4) of Table 2, we include pool dummies which increase the R^2 to 0.92, showing that there are substantial average differences in DebtRank across pools that are not captured by the other features. The coefficients on the pool dummies (e.g., ETH and USDC) represent the average difference in DebtRank for each pool relative to the reference pool (DAI), holding all other variables constant. For example, the positive and significant coefficient for USDC indicates that, on average, USDC pools have higher DebtRank than

[10] Results for all shock levels from 10% to 50% are provided in Subsection B.1.

DAI pools, after controlling for all other factors.

Table 2 Regression Results - DebtRank 10% Shock

Dependent Variable: DebtRank	**(1)**	**(2)**	**(3)**	**(4)**
Constant	0.368	0.370	0.338	0.255
	(0.002)	(0.002)	(0.002)	(0.005)
Lenders' in-degree (wavg)	-0.030	-0.042	-0.013	0.015
	(0.003)	(0.003)	(0.002)	(0.002)
Lenders' out-degree (wavg)	0.221	0.268	0.166	0.063
	(0.003)	(0.003)	(0.005)	(0.005)
Borrowers' in-degree (wavg)	-0.076	-0.048	-0.048	-0.038
	(0.004)	(0.004)	(0.003)	(0.002)
Borrowers' out-degree (wavg)	0.037	0.027	0.084	0.033
	(0.004)	(0.004)	(0.004)	(0.003)
Hub		-0.003	-0.048	-0.019
		(0.003)	(0.002)	(0.002)
Closeness		-0.044	-0.009	-0.006
		(0.002)	(0.001)	(0.001)
Out-weight HHI		-0.022	-0.072	-0.061
		(0.003)	(0.003)	(0.003)
In-weight HHI		-0.068	-0.068	-0.031
		(0.003)	(0.003)	(0.002)
Equity share			0.027	-0.011
			(0.002)	(0.002)
External assets share			0.025	0.012
			(0.005)	(0.004)
Size share			0.118	-0.001
			(0.004)	(0.004)
Borrowers' self-borrowing share (wavg)			0.048	0.077
			(0.003)	(0.003)
Borrowers' borrowing share (wavg)			0.053	0.018
			(0.004)	(0.003)
Lenders' equity (wavg)			0.034	0.043
			(0.002)	(0.002)
Borrowers' equity (wavg)			0.059	0.034
			(0.002)	(0.002)
Lenders' deposit share (wavg)			-0.015	0.035
			(0.003)	(0.002)
ETH				0.214
				(0.010)
BTC				0.174
				(0.011)
USDC				0.230
				(0.005)
USDT				-0.135
				(0.009)
R^2	0.584	0.676	0.842	0.919
Adj. R^2	0.584	0.676	0.842	0.918
F-statistic	1765.0	1312.0	1673.0	2834.0
N obs	5035	5035	5035	5035

Note: Each column reports the results of a separate OLS regression. In column (4), the reference pool is DAI. Robust standard errors are used to control for heteroskedasticity.

5.4 Variance Decomposition

To further stress the relevance of the topological features identified in the regression analysis, we perform a variance decomposition of the model's predictions over time.[11] While the regression table demonstrates that topological variables—especially those capturing network connectivity—are the primary drivers of DebtRank, the table itself provides only a static, aggregate view of feature importance. To analyze changes over time, we decompose the model's explained variance by feature and track its evolution on a monthly basis. For each month, we compute the variance of each feature's contribution to the predicted DebtRank—defined as the product of its standardized value and estimated coefficient—across all pools. These

[11] Variance decomposition results for all shock levels from 20% to 50% are provided in Subsection B.1.

variances are then normalized so that, for each month, the sum of all features' contributions equals 100%.

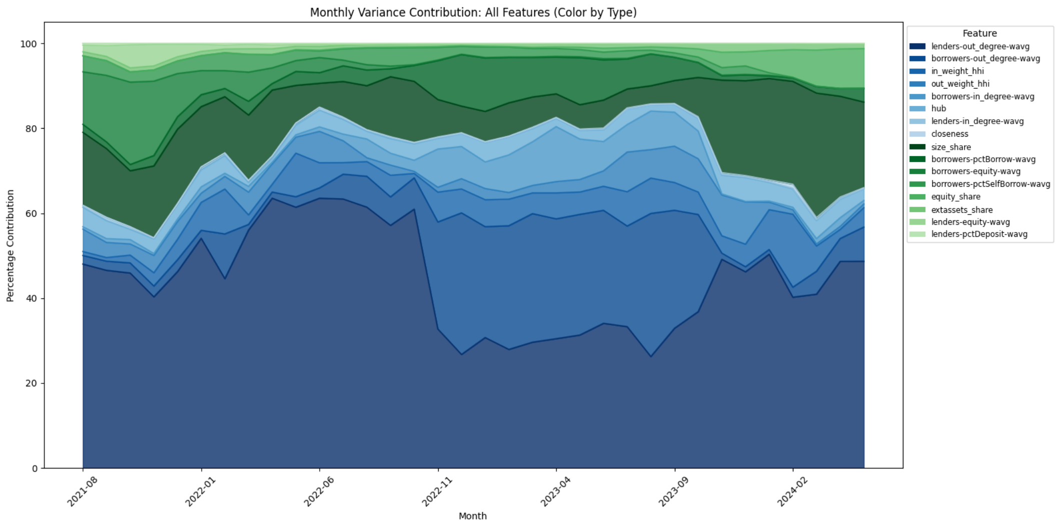


Figure 6 Monthly variance decomposition of DebtRank predictions by feature type - 10% shock.

Figure 6 presents a stacked area plot showing the monthly percentage contribution of each feature to the model's explained variance, with colors indicating feature type (topological in blue, financial in green). This visualization provides a longitudinal perspective on the relative importance of each feature group. The figure highlights that topological features consistently account for the largest share of explained variance in DebtRank throughout the sample period.

Among the set of topological features, *lenders' out-degree (wavg)* stands out as the most relevant, accounting for more than 40% of the explained variance over most of the sample. Recall that *lenders' out-degree* is constructed by assigning to each lender the number of pools from which they borrowed, and aggregating these values by weighting each lender according to the size of their loan to the shocked pool. Lenders' out-degree thus captures lenders' connectivity. Interestingly, its explanatory power surpasses that of more commonly used centrality measures, such as *hub* or *closeness*, underscoring the importance of considering not only the centrality of the affected node, but also the connectivity of its neighbors. For the same reason, *borrowers' out-degree* also shows some explanatory power, though to a lesser extent than *lenders' out-degree* because borrowers benefit from a drop in the price of their borrowed tokens, whereas lenders enter a distressed state and begin propagating the price shock when the value of their loans, and thus of their collateral—falls.

Financial features, while significant, contribute a smaller and relatively stable share. The temporal evolution also shows that the dominance of topological features is robust to changes in market conditions or network structure. This dynamic decomposition thus reinforces the main conclusion from the regression table: Systemic risk in the protocol is primarily determined by network topology, with lender connectivity playing a particularly critical role, while financial metrics are of secondary importance.

5.5 Trend Decomposition

While the variance decomposition underscores the persistent dominance of topological features in explaining cross-sectional variation in DebtRank, it does not indicate which features are most influential in driving the downward trend in systemic risk over time (see Figure 5). To complement this analysis and provide further evidence of the relevance of topological features, we examine the trend decomposition, which highlights the relative contribution of each feature to the decline of the DebtRank scores over the sample period.

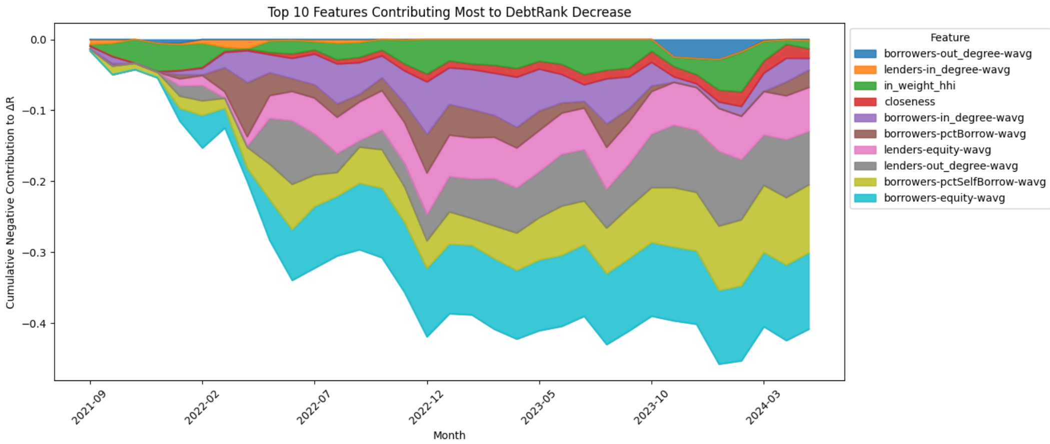


Figure 7 Top 10 Features Contributing Most to DebtRank Decrease (Largest Contributor at Bottom) - 10% shock.

Figure 7 illustrates the cumulative negative contribution of the top 10 features to the decline in DebtRank over time. For each month, a feature's contribution is calculated as the product of its standardized value and its estimated regression coefficient, considering only negative values and accumulating them over time. The features are stacked such that the largest contributor appears at the bottom, with each colored area representing that feature's share of the total DebtRank reduction at a given point. Figure 7, therefore, highlights which variables are most instrumental in reducing systemic risk. It shows that topological features once again rank among the most influential, underscoring the importance of network structure in mitigating systemic risk over the sample period.

6 Robustness Checks

6.1 Nonlinear Models

We conduct a residual analysis to assess the adequacy of the linear regression model and motivate the exploration of nonlinear effects. Figure 8 displays the main diagnostic plots for the model with robust standard errors, which account for potential heteroskedasticity and provide more reliable inference. The left panel shows residuals plotted against fitted values, while the right panel shows residuals against the actual DebtRank, both for the 10% shock scenario. These plots allow for visual inspection of systematic patterns, non-linearity, or heteroskedasticity that may indicate model misspecification. The use of robust standard errors ensures that the results remain valid even if the variance of the errors is not constant.

Visual inspection of these plots reveals several signs of model misspecification. The residuals display clear nonlinear patterns and heteroskedasticity, rather than being randomly

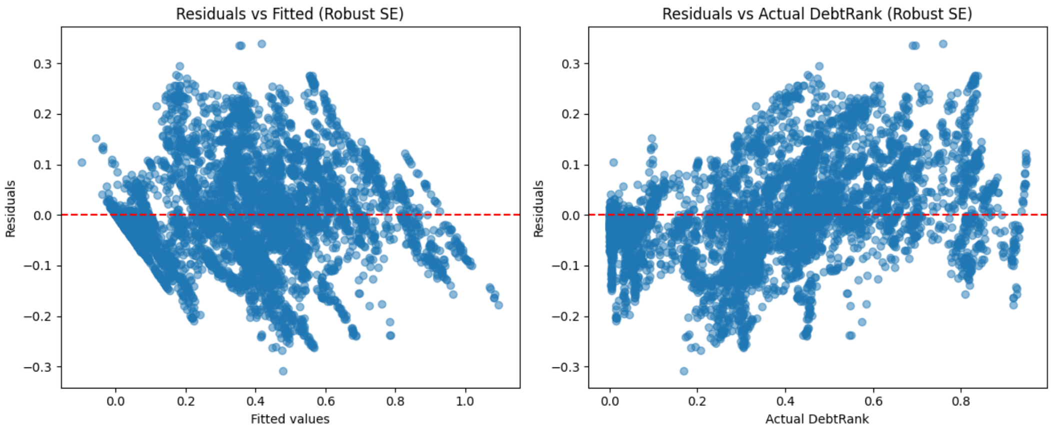


Figure 8 Residuals vs Fitted Values and Actual DebtRank (Robust Standard Errors).

scattered around zero. This suggests that the linear model does not fully capture the relationship between the predictors and the outcome variable. The presence of curved or U-shaped patterns in the residuals indicates the potential benefit of including quadratic or higher-order terms, or using more flexible nonlinear models (such as splines, decision trees, or random forests).

Table 3 presents results from both linear and nonlinear models, highlighting the improvement in explanatory power when accounting for nonlinearities and interactions.[12] Column (2) in Table 3 reports results from an OLS regression that includes interaction terms between key topological and financial features, as well as pool dummies and their interactions. This richer specification leads to some improvement in explanatory power, with R^2 increasing from 0.84 in the Lasso model to 0.92 in the interaction model. The inclusion of quadratic terms in column (3) further improves the fit, confirming the presence of nonlinear effects in the data. Quantile regression in column (4) provides a robust alternative that is less sensitive to outliers and heteroskedasticity, while tree-based models in columns (5) and (6) capture complex, nonlinear relationships and higher-order interactions without requiring explicit functional form assumptions.

While the inclusion of nonlinearities and interaction terms leads to a noticeable, albeit modest, increase in R^2 compared to the best-performing linear models, the set of relevant features remains largely consistent across specifications, suggesting that the main drivers of DebtRank propagation are robust to model choice.

6.2 Stablecoin vs. Crypto Pools

Table 4 presents the results of OLS regressions explaining DebtRank following a 10% price shock, estimated separately for lending pools grouped by asset type.[13] Columns (1) and (2) report results for stablecoin pools (DAI, USDT, and USDC), while columns (3) and (4) correspond to crypto pools (ETH and BTC). All variables are standardized, so coefficients are directly comparable both within and across groups.

[12] Nonlinear regression results for the 50% shock scenario are reported in Subsection B.2.

[13] Robustness checks excluding self-borrowing users are reported in Subsection B.3. Also, to account for the distinct treatment of USDT, which cannot be used as collateral, we also report robustness checks excluding the USDT pool across all shock levels in Subsection B.4.

Table 3 Nonlinear Regression Results - DebtRank 10% Shock

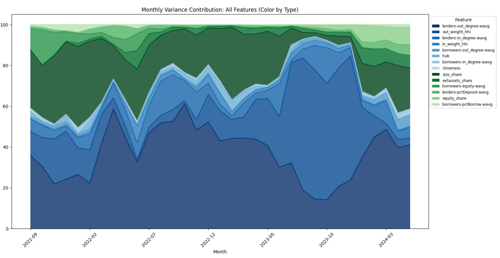
	Coefficients				Features' Importance	
Dependent Variable: DebtRank	**(1) Lasso**	**(2) Interaction Effects**	**(3) Quadratic Terms**	**(4) Quantile Regression (0.5)**	**(5) Decision Tree**	**(6) Random Forest**
Constant	0.338	0.223	0.372	0.329		
	(0.002)	(0.005)	(0.005)	(0.001)		
Lenders' in-degree (wavg)	-0.013	0.010	-0.015	-0.019	0.015	0.0139
	(0.002)	(0.002)	(0.003)	(0.002)		
Lenders' out-degree (wavg)	0.166	-0.061	0.214	0.156	**0.451**	**0.452**
	(0.005)	(0.009)	(0.006)	(0.004)		
Lenders' out-degree (wavg)^2			-0.011			
			(0.003)			
Borrowers' in-degree (wavg)	-0.048	-0.038	-0.050	-0.036	0.003	0.0027
	(0.003)	(0.002)	(0.003)	(0.003)		
Borrowers' out-degree (wavg)	0.084	0.035	0.082	0.072	0.002	0.0025
	(0.004)	(0.003)	(0.005)	(0.003)		
Borrowers' out-degree (wavg)^2			-0.004			
			(0.001)			
Hub	-0.048	-0.012	-0.021	-0.052	0.002	0.0017
	(0.002)	(0.002)	(0.002)	(0.002)		
Authority			0.001		0.000	0.0002
			(0.002)			
Closeness	-0.009	-0.005	-0.006	-0.006	0.000	0.0002
	(0.001)	(0.001)	(0.002)	(0.001)		
Closeness^2			0.000			
			(0.000)			
Pagerank					0.024	0.0309
Out-weight HHI	-0.072	-0.048	-0.133	-0.069	0.026	0.0194
	(0.003)	(0.003)	(0.005)	(0.003)		
Out-weight HHI^2			0.033			
			(0.003)			
In-weight HHI	-0.068	-0.035	-0.089	-0.070	0.038	0.0418
	(0.003)	(0.002)	(0.004)	(0.002)		
In-weight HHI^2			0.023			
			(0.002)			
Equity share	0.027	-0.022	0.036	0.027	0.379	0.373
	(0.002)	(0.002)	(0.002)	(0.001)		
External assets share	0.025	-0.005	0.019	0.026	0.009	0.0056
	(0.005)	(0.004)	(0.006)	(0.004)		
External assets share^2			-0.030			
			(0.004)			
Size share	0.118	0.008	0.083	0.125	0.006	0.0066
	(0.004)	(0.004)	(0.005)	(0.003)		
Size share^2			-0.088			
			(0.003)			
Borrowers' self-borrowing share (wavg)	0.048	0.078	0.029	0.060		0.0088
	(0.003)	(0.003)	(0.003)	(0.002)		
Borrowers' borrowing share (wavg)	0.053	0.019	0.038	0.048	0.014	0.0083
	(0.004)	(0.003)	(0.004)	(0.003)		
Lenders' equity (wavg)	0.034	0.027	0.069	0.032	0.005	0.0080
	(0.002)	(0.002)	(0.003)	(0.002)		
Borrowers' equity (wavg)	0.059	0.033	0.058	0.059	0.024	0.0196
	(0.002)	(0.002)	(0.002)	(0.002)		
Lenders' deposit share (wavg)	-0.015	0.022	0.009	-0.034	0.002	0.0041
	(0.003)	(0.003)	(0.004)	(0.003)		
ETH		0.184				
		(0.011)				
BTC		0.141				
		(0.014)				
USDC		0.261				
		(0.007)				
USDT		-0.097				
		(0.019)				
Lenders' out-degree × ETH		0.209				
		(0.0111)				
Lenders' out-degree × BTC		0.190				
		(0.013)				
Lenders' out-degree × USDC		0.120				
		(0.011)				
Lenders' out-degree × USDT		0.129				
		(0.014)				
R^2 / Pseudo R^2	0.842	0.924	0.869	0.636	0.618	
Adj. R^2	0.842	0.924	0.868	–	–	
N obs	5035	5035	5035	5035	5035	5035

Note: Column (2) reports OLS with pool and interaction terms. Other columns report Lasso+Quadratic, Quantile, Decision Tree, and Random Forest. Quadratic terms are denoted with ^{2}. Interaction terms are denoted with ×. In column (2), the reference pool is DAI. Blank entries indicate variables not selected by the Lasso procedure. Robust standard errors are used to control for heteroskedasticity.

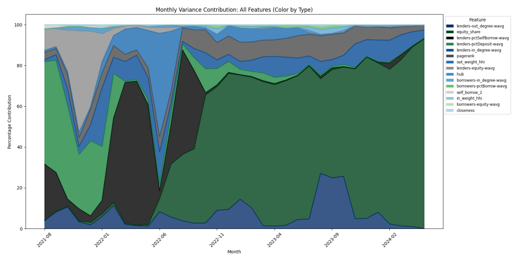
This table enables a direct comparison of the relative importance and direction of key topological and financial features in driving systemic risk across different pool types. Among topological variables, *lenders' out-degree (wavg)* stands out as a consistently strong positive predictor of DebtRank in both stablecoin and crypto pools, with larger coefficients in the stablecoin group (e.g., 0.145 in column 1) than in the crypto group (0.060 in column 3). Conversely, *lenders' in-degree (wavg)* generally has a negative or weak effect, with a stronger negative association in stablecoin pools. Other topological measures, such as the *hub* and *closeness* centrality scores, tend to have larger negative coefficients for stablecoin pools. Overall, these findings suggest that the systemic risk of pools with more outward connections—such as stablecoins, which tend to be more heavily borrowed—is particularly influenced by topolgical features.

Financial features also play an important role, but their relevance varies by group. For example, *equity share* is positively associated with DebtRank in stablecoin pools but negatively associated in crypto pools, suggesting that higher equity increases systemic risk among stablecoins but mitigates it among cryptos. The *size share* is only significant in stablecoin pools, whereas the *borrowers' equity (wavg)* is positive in both groups but with much larger coefficients in stablecoins.

Pool dummies (e.g., USDC, USDT, and BTC) capture pool-specific effects and further highlight heterogeneity across assets. These dummies allow the model to account for baseline differences in systemic risk across pools, providing a nuanced view of how network structure and financial characteristics interact with asset type to shape systemic vulnerability. The model's fitness is high in all specifications, with values of R^2 greater than 0.86 for stablecoins and 0.93 for cryptos, indicating that the selected characteristics explain a substantial portion of the variation in systemic risk.



(a) Stablecoins



(b) Crypto

Figure 9 Monthly variance contribution of features for (a) stablecoins and (b) crypto pools.

Figure 9 compares the monthly variance contributions of model features for stablecoin and crypto lending pools. The results reveal a clear difference in the drivers of systemic risk across these two segments. For stablecoins, the *lenders' out-degree* consistently emerges as the most important predictor, accounting for a substantially larger share of explained variance than any other feature. This suggests that the connectivity of lenders plays a dominant and persistent role in shaping the systemic risk associated with stablecoin pools.

In contrast, feature importance is more evenly distributed for crypto pools, with financial variables such as *equity share* contributing significantly. This indicates that systemic risk in crypto pools is driven by a broader set of factors, with a much stronger influence of pool-level financial characteristics.

Table 4 Regression Results by Pools - DebtRank 10% Shock

Dependent Variable: DebtRank	Stablecoins: DAI, USDT, USDC		Cryptos: ETH, BTC	
	(1)	(2)	(3)	(4)
Constant	0.216	0.289	0.507	0.598
	(0.002)	(0.005)	(0.002)	(0.005)
Lenders' in-degree (wavg)	-0.082	-0.008	0.036	0.027
	(0.003)	(0.003)	(0.002)	(0.002)
Lenders' out-degree (wavg)	0.145	0.056	0.060	0.078
	(0.005)	(0.004)	(0.004)	(0.004)
Borrowers' in-degree (wavg)	-0.028	-0.021	-0.007	-0.014
	(0.003)	(0.002)	(0.002)	(0.002)
Borrowers' out-degree (wavg)	0.027	0.004		
	(0.003)	(0.002)		
Pagerank			-0.049	-0.515
			(0.007)	(0.029)
Hub	-0.034	-0.012	-0.009	0.008
	(0.003)	(0.002)	(0.002)	(0.002)
Closeness	-0.003	-0.002	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Out-weight HHI	-0.122	-0.072	-0.048	-0.035
	(0.004)	(0.003)	(0.005)	(0.004)
In-weight HHI	-0.040	-0.034	-0.004	
	(0.004)	(0.003)	(0.002)	
Equity share	0.025	-0.032	-0.082	-0.075
	(0.002)	(0.002)	(0.002)	(0.002)
Size share	0.139	0.039		
	(0.004)	(0.003)		
Borrowers' self-borrowing share (wavg)			0.009	0.023
			(0.003)	(0.002)
Borrowers' borrowing share (wavg)	0.030	0.008	-0.007	-0.008
	(0.004)	(0.003)	(0.002)	(0.002)
Lenders' equity (wavg)			0.038	
			(0.002)	
Borrowers' equity (wavg)	0.076	0.057	0.005	0.013
	(0.003)	(0.002)	(0.002)	(0.002)
Lenders' deposit share (wavg)	-0.046	0.018	0.034	0.007
	(0.004)	(0.003)	(0.002)	(0.003)
USDC		0.124		
		(0.005)		
USDT		-0.251		
		(0.009)		
BTC				-0.436
				(0.025)
R^2	0.867	0.935	0.933	0.935
Adj. R^2	0.867	0.935	0.933	0.934
F-statistic	1329.000	2575.000	1844.000	2022.000
N obs	2862	2862	1990	1990

Note: Each column reports the results of a separate OLS regression. In column (2), the reference pool is DAI; in column (4), it is ETH. Blank entries indicate variables not selected by the Lasso procedure. Robust standard errors are used to control for heteroskedasticity.

7 Conclusion

This study provides a comprehensive empirical analysis of systemic risk in decentralized lending protocols, focusing on Compound. We show that systemic risk is highly concentrated in a small subset of lending pools, highlighting the importance of network-aware monitoring and intervention strategies. By applying the Spatial Lag of X (SLX) model to this novel setting, we demonstrate its effectiveness in capturing shock propagation driven by both financial heterogeneity and network topology. The use of high-frequency, network-structured data enables a dynamic and interpretable understanding of how localized shocks may amplify across the system.

Our results indicate that topological characteristics, particularly network connectivity, are more informative than financial metrics alone in predicting systemic vulnerability as measured by DebtRank. Among these, lenders' out-degree emerges as the most powerful single predictor of distress transmission, underscoring the importance of relational exposure over balance sheet size. These findings underscore the need for continuous systemic risk assessment in DeFi systems, even in environments with full transactional transparency. From a policy perspective, targeting interventions toward systemically important pools could be an effective way to mitigate contagion and enhance protocol resilience.

While our approach offers valuable insights, it abstracts from off-protocol and cross-platform exposures. Future research could extend this framework by incorporating multi-protocol dependencies, asset price dynamics, or endogenous feedback mechanisms to capture more complex forms of financial contagion.

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A Feature Extraction

The bipartite network represents liability relationships between user and lending pool nodes, denoted as L_{ij}, where node i has a liability to node j. Based on the daily asset prices, the edge weights correspond to the liability amounts converted to U.S. dollars.

Node features. We extract node-level features as summarized in Table 5. We further compute the share of each lending pool's equity, external assets, and size to assess the relative scale of each lending pool. These shares are calculated by normalizing each variable by the total across all pool nodes, i.e., $share_j = variable_j / \sum_k variable_k$, where j indexes a specific lending pool and k ranges over all pools.

In addition to these attributes, we compute several centrality measures for each node to characterize its structural role in the network:

- *Closeness Centrality*, estimated using approximate algorithms provided by the NetworKit library [5], due to computational limitations of exact methods;
- *Hubs and Authorities*, computed via the HITS algorithm [30];

Table 5 Node features for users and lending pools

Feature	User Node	Lending Pool Node
In-degree	Number of deposited assets	Number of borrowing users
In-weight	Total deposited amount	Total borrowed amount
In-weight HHI	Herfindahl index of deposited assets	Herfindahl index of borrowing users
Out-degree	Number of borrowed assets	Number of depositing users
Out-weight	Total borrowed amount	Total deposited amount
Out-weight HHI	Herfindahl index of borrowed assets	Herfindahl index of depositing users
In/Out Ratio	Deposit-to-borrow ratio	Borrow-to-deposit ratio
Health Ratio	Health ratio of users	N/A
External assets	0 (assuming no external assets)	Available liquidity (cash) + reserves
Equity	External assets + In-weight – Out-weight	
Size	In-weight + Out-weight	
% Self-borrowing	Percentage of self-borrowed amount	

Note: The Herfindahl-Hirschman Index (HHI) is calculated as $HHI = \sum_i s_i^2$, where s_i is the share of value associated with asset i (for users: deposits or borrows; for pools: users depositing or borrowing). A higher HHI indicates greater concentration.

- *PageRank*, which we use as a practical proxy for eigenvector centrality, given its faster convergence and scalability [39].

Edge features. For each user–pool edge, we compute the share of deposits and borrows to quantify the user's relative exposure to the pool. These features are defined as:

$$\text{shareDeposit}_{u,i} = \frac{\text{deposit}_{u,i}}{\sum_u \text{deposit}_{u,i}}, \qquad \text{shareBorrow}_{u,i} = \frac{\text{borrow}_{u,i}}{\sum_u \text{borrow}_{u,i}}, \tag{13}$$

where $\text{deposit}_{u,i}$ and $\text{borrow}_{u,i}$ denote the amounts deposited to or borrowed from pool i by user u. These ratios capture the proportion of a user's activity attributed to a specific pool.

Lenders and borrowers features: We compute the weighted average of node attributes for lenders (nodes with outgoing edges to the pool) and borrowers (nodes with incoming edges from the pool), using the out-weight and in-weight, respectively, as weighting factors. This allows us to capture the average characteristics of users interacting with each pool, adjusted by the magnitude of their deposited or borrowed amounts.

Table 6 lists the features included in the regression models. The features include topological metrics and financial attributes for the shocked pool, as well as user-aggregated statistics for lenders and borrowers.

B Robustness Check

B.1 Regression Results Across Shock Intensities (10%–50%

To evaluate how the relationship between network and financial features and systemic risk evolves under increasing stress, we estimate separate OLS regressions for each level of simulated price shock ranging from 10% to 50%. Table 7 presents the results of these regressions, with each column corresponding to a different shock intensity. The model specification remains consistent across columns, with predictors selected via Lasso re-estimation for each shock level.

The results demonstrate strong consistency in both the direction and significance of key variables. *Lenders' out-degree*, *out-weight HHI*, and *borrowers' self-borrowing share*

Table 6 Features used in the regression models. Weighted averages (wavg) are computed over lenders and borrowers using deposit and borrow amounts, respectively.

Feature Type	Shocked Pool	Lenders (wavg)	Borrowers (wavg)
Topological Features			
In-Degree		✓	✓
Out-Degree		✓	✓
In/Out Ratio	✓	✓	✓
In-Weight HHI		✓	✓
Out-Weight HHI		✓	✓
PageRank	✓	✓	✓
Hub Score	✓	✓	✓
Authority Score	✓	✓	✓
Closeness Centrality	✓	✓	✓
Financial Features			
Equity Share	✓		
External Asset Share	✓		
Size Share	✓		
Utilization Rate	✓		
External Assets		✓	✓
Equity		✓	✓
% Self-Borrow		✓	✓
Deposit share in shocked pool		✓	
Borrow share from shocked pool			✓
Health Ratio		✓	✓

remain positively and significantly associated with systemic risk across all shock levels. This confirms that network centrality and exposure concentration on the lending side are persistent amplifiers of systemic risk. Conversely, *equity share* and *in-weight HHI* show consistently negative coefficients, indicating their stabilizing role even under extreme stress.

While the magnitude of several coefficients increases with shock intensity, some financial variables display more dynamic behavior. *USDT* has an increasingly strong negative effect on DebtRank as shock severity rises, with its coefficient dropping from -0.135 under the 10% shock to -0.561 at 50%. This suggests that USDT becomes a major driver of systemic vulnerability in high-stress environments, possibly due to its structural role in liquidity channels or counterparty risk concentration. *ETH* exhibits a decreasing positive effect, with its coefficient falling from 0.214 (10%) to just 0.039 (50%). This indicates that ETH's contribution to systemic risk diminishes under extreme stress, potentially due to greater diversification or lower leverage exposure in ETH pools. *BTC* and *USDC* show similar attenuation patterns, although they remain positively associated with DebtRank. In contrast, the *external assets share* drops out entirely by the 50% specification, suggesting a loss of explanatory power as liquidity dries up or valuation metrics become less predictive.

Despite these shifts, the overall explanatory power of the models remains high and stable. The R^2 values range narrowly between 0.914 and 0.923, even under the strongest simulated shock. This reinforces the conclusion that systemic risk is structurally driven by a core set of network and financial characteristics whose influence is robust to deteriorating market conditions.

The variance decomposition of model predictions, computed as in Figure 10, also exhibits consistent patterns across shocks: network topology remains the dominant explanatory channel, with *lenders' out-degree* accounting for the largest share of explained variance over time.

Table 7 Regression Results - DebtRank All Shocks

Dependent Variable: DebtRank	10%	20%	30%	40%	50%
Constant	0.255	0.383	0.514	0.587	0.615
	(0.006)	(0.005)	(0.006)	(0.007)	(0.005)
Lenders' in-degree (wavg)	0.015	0.023	0.025	0.031	0.029
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lenders' out-degree (wavg)	0.063	0.079	0.070	0.059	0.054
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Borrowers' in-degree (wavg)	-0.038	-0.050	-0.046	-0.046	-0.043
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Borrowers' out-degree (wavg)	0.033	0.033	0.038	0.039	0.037
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Hub	-0.019	-0.008	-0.001	-0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Closeness	-0.006	-0.011	-0.007	-0.005	-0.005
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Out-weight HHI	-0.061	-0.078	-0.081	-0.076	-0.077
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
In-weight HHI	-0.031	-0.030	-0.024	-0.018	-0.015
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Equity share	-0.011	-0.032	-0.058	-0.071	-0.079
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
External assets share	0.012	0.002	0.011	0.008	
	(0.003)	(0.005)	(0.005)	(0.005)	
Size share	-0.001	-0.043	-0.077	-0.085	-0.088
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Borrowers' self-borrowing share (wavg)	0.077	0.105	0.076	0.059	0.047
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Borrowers' borrowing share (wavg)	0.018	0.008	0.003	0.003	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Lenders' equity (wavg)	0.043		0.012	0.007	0.005
	(0.002)		(0.002)	(0.002)	(0.002)
Borrowers' equity (wavg)	0.034	0.037	0.024	0.021	0.021
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Lenders' deposit share (wavg)	0.035	0.050	0.053	0.051	0.050
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
ETH	0.214	0.224	0.111	0.093	0.039
	(0.010)	(0.010)	(0.010)	(0.020)	(0.009)
USDC	0.230	0.252	0.205	0.171	0.135
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)
USDT	-0.135	-0.271	-0.431	-0.483	-0.561
	(0.011)	(0.010)	(0.011)	(0.018)	(0.009)
WBTC	0.174	0.193	0.118	0.136	0.082
	(0.011)	(0.011)	(0.012)	(0.032)	(0.010)
R^2	0.919	0.914	0.918	0.921	0.923
Adj. R^2	0.918	0.913	0.917	0.921	0.923
F-statistic	5781.0	7541.0	6112.0	5101.0	3519.0
N obs	5035	5390	5370	5370	5585

Note: Each column reports the results of a separate OLS regression. The reference pool is DAI. Blank entries indicate variables not selected by the Lasso procedure. Robust standard errors are used to control for heteroskedasticity.

B.2 Robustness Check: Nonlinear Regression Results (50% Shock)

Table 8 presents the results of nonlinear regressions estimating the determinants of systemic risk, measured by DebtRank, under a 50% shock scenario. Columns (1)–(3) show the coefficients from OLS models using Lasso-selected variables, including interaction and quadratic terms. Columns (5) and (6) report feature importance scores from decision tree and random forest models. The results highlight the key role of *lenders' out-degree*, *equity share*, and interaction effects with token types in shaping systemic impact.

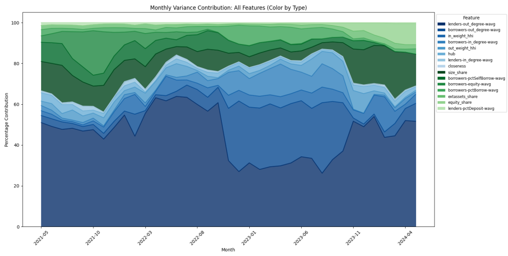
B.3 Regression Results Across Shock Levels Excluding Self-Borrowing

Table 9 presents OLS regression results estimating the determinants of systemic risk (DebtRank) across varying shock intensities from 10% to 50%, excluding the effect of self-borrowing. Self-borrowing is excluded to focus on external contagion channels and to avoid bias from internal borrowing relationships. The models use Lasso for variable selection,

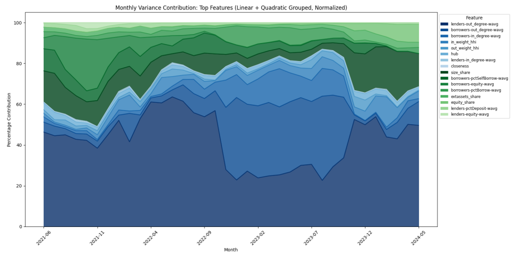
Table 8 Nonlinear Regression Results - DebtRank 50% Shock

	Coefficients			Features' Importance	
Dependent Variable: DebtRank	**(1) Lasso**	**(2) Interaction Effects OLS**	**(3) Lasso + Quadratic Terms**	**(5) Decision Tree**	**(6) Random Forest**
Constant	0.544 (0.002)	0.6075 (0.005)	0.7149 (0.005)		
Lenders' in-degree (wavg)	-0.018 (0.003)	0.0224 (0.002)		0.0049	0.0046
Lenders' out-degree (wavg)	0.212 (0.004)	0.0102 (0.011)	0.2590 (0.003)	**0.6524**	**0.6494**
Borrowers' in-degree (wavg)	-0.072 (0.004)	-0.0415 (0.002)	-0.0707 (0.003)	0.0026	0.0023
Borrowers' out-degree (wavg)	0.108 (0.005)	0.0393 (0.003)	0.0636 (0.003)	0.0053	0.0043
Hub	-0.030 (0.003)	0.0041 (0.002)	-0.0031 (0.002)	0.0039	0.0090
Closeness	-0.005 (0.002)	-0.0054 (0.001)	0.0022 (0.003)	0.0001	0.0002
Out-weight HHI	-0.034 (0.005)	-0.0741 (0.003)	-0.0932 (0.005)	0.0046	0.0122
In-weight HHI	-0.048 (0.003)	-0.0177 (0.002)	-0.0521 (0.004)	0.0154	0.0131
Equity share	0.019 (0.002)	-0.0843 (0.003)	-0.0003 (0.003)	0.2034	0.1970
External assets share	-0.005 (0.004)			0.0082	0.0085
Size share	0.111 (0.005)	-0.0929 (0.004)		0.0056	0.0074
Borrowers' self-borrowing share (wavg)	0.070 (0.003)	0.0469 (0.002)	0.0262 (0.003)	0.0290	0.0226
Borrowers' borrowing share (wavg)	0.052 (0.005)	0.0066 (0.003)		0.0032	0.0041
Lenders' equity (wavg)	-0.053 (0.002)	0.0049 (0.002)	0.0341 (0.003)	0.0053	0.0041
Borrowers' equity (wavg)	0.077 (0.002)	0.0179 (0.001)	0.0520 (0.002)	0.0039	0.0066
Lenders' deposit share (wavg)	-0.050 (0.004)	0.0477 (0.002)	0.0477 (0.002)	0.0017	0.0046
ETH		0.0215 (0.009)			
USDC		0.1405 (0.006)			
USDT		-0.2905 (0.027)			
BTC		0.1215 (0.012)			
Lenders' out-degree x ETH		0.0721 (0.012)			
Lenders' out-degree x USDC		0.0286 (0.012)			
Lenders' out-degree x USDT		0.2476 (0.022)			
Lenders' out-degree x BTC		0.0191 (0.013)			
Lenders' out-degree (wavg)^2			-0.0967 (0.002)		
Extassets share^2			-0.0717 (0.004)		
Size share^2			-0.0790 (0.004)		
In-weight HHI^2			0.0150 (0.002)		
Out-weight HHI^2			-0.0013 (0.003)		
Closeness^2			-0.0003 (0.000)		
R^2 / Pseudo R^2	0.784	0.926	0.833	0.594	–
Adj. R^2	0.784	0.926	0.832	–	–
N obs	5035	5585	5585	5035	5585

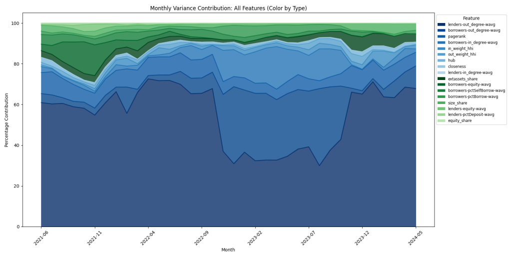
Note: Each column reports the results of a separate OLS regression. In column (2), the reference pool is DAI. Blank entries indicate variables not selected by the Lasso procedure. Robust standard errors are used to control for heteroskedasticity.



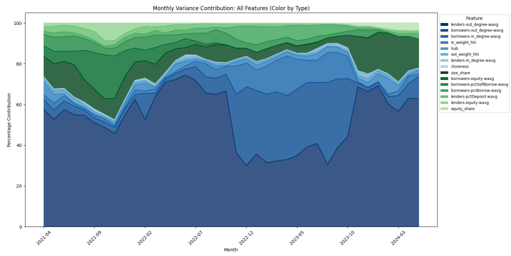
(a) Shock 20%



(b) Shock 30%



(c) Shock 40%



(d) Shock 50%

Figure 10 Monthly variance decomposition of DebtRank predictions by feature type for different shock sizes.

with DAI as the reference pool. Key explanatory variables include network features, equity and asset shares, and different cryptocurrency exposures. The high adjusted R^2 values indicate strong explanatory power across all shock levels.

B.4 Regression Results Excluding USDT Pool (All Shock Levels)

Table 10 reports the results of OLS regressions estimating the determinants of systemic risk—measured via DebtRank—following exogenous price shocks of varying magnitudes (10%, 20%, 30%, 40%, and 50%), excluding USDT. This is because USDT cannot be used as collateral for borrowing. As a result, it plays a minimal role in the contagion dynamics central to systemic risk propagation.

Results show that both topological features (e.g., *lenders' out-degree*, *borrowers' in-degree*) and financial variables (e.g., *equity share*, *self-borrowing*) significantly influence systemic risk. Asset dummies for ETH, USDC, and BTC indicate a higher baseline DebtRank, compared to DAI. The models demonstrate strong explanatory power, with R^2 values between 0.76 and 0.86, though predictive strength slightly decreases at higher shock magnitudes.

Table 9 Regression Results - DebtRank All Shocks - No Self-Borrowing

Dependent Variable: DebtRank	10%	20%	30%	40%	50%
Constant	0.163	0.253	0.363	0.358	0.615
	(0.005)	(0.006)	(0.006)	(0.007)	(0.005)
Lenders' in-degree (wavg)	0.019	0.007			0.029
	(0.002)	(0.002)			(0.002)
Lenders' out-degree (wavg)	0.044	0.027	0.105	0.020	0.054
	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Borrowers' in-degree (wavg)	-0.027	-0.023		-0.031	-0.043
	(0.002)	(0.003)		(0.003)	(0.002)
Borrowers' out-degree (wavg)	0.024	0.015	-0.008	0.020	0.037
	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)
Pagerank					
Hub	-0.010	-0.009	-0.018	-0.021	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Closeness	-0.005				-0.005
	(0.001)				(0.001)
Out-weight HHI	-0.042	-0.066	-0.037	-0.049	-0.077
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
In-weight HHI	-0.012	-0.022	-0.009	-0.009	-0.015
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
Equity share	-0.006	-0.024	-0.040	-0.033	-0.079
	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)
External assets share	0.024	0.001		0.020	
	(0.003)	(0.004)		(0.004)	
Size share	-0.024	-0.071	-0.086	-0.071	-0.088
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Borrowers' self-borrowing share (wavg)	0.042	0.062		0.033	0.047
	(0.002)	(0.002)		(0.003)	(0.002)
Borrowers' borrowing share (wavg)	0.024	0.012			0.004
	(0.002)	(0.003)			(0.003)
Lenders' equity (wavg)		0.008		0.012	0.005
		(0.002)		(0.002)	(0.002)
Borrowers' equity (wavg)	0.027	0.025	0.019	0.019	0.021
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Lenders' deposit share (wavg)	0.025	0.039	0.016	0.019	0.050
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
ETH	0.209	0.289	0.156	0.231	0.039
	(0.009)	(0.010)	(0.009)	(0.011)	(0.009)
USDC	0.257	0.287	0.269	0.267	0.135
	(0.006)	(0.007)	(0.009)	(0.009)	(0.006)
USDT	-0.103	-0.287	-0.331	-0.372	-0.561
	(0.009)	(0.012)	(0.010)	(0.012)	(0.009)
BTC	0.209	0.333	0.209	0.320	0.082
	(0.010)	(0.010)	(0.010)	(0.013)	(0.011)
R^2	0.884	0.885	0.883	0.904	0.923
Adj. R^2	0.883	0.885	0.883	0.903	0.923
F-statistic	4864.0	6353.0	7037.0	5946.0	4660.0
N obs	4975	5390	4790	4790	5585

Note: Each column reports the results of a separate OLS regression. The reference pool is DAI. Blank entries indicate variables not selected by the Lasso procedure. Robust standard errors are used to control for heteroskedasticity.

Table 10 Regression Results - DebtRank All Shocks - No USDT

Dependent Variable: DebtRank	10%	20%	30%	40%	50%
Constant	0.285	0.416	0.503	0.351	0.421
	(0.006)	(0.007)	(0.007)	(0.008)	(0.005)
Lenders' in-degree (wavg)	0.017	0.026	0.047	0.039	0.022
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Lenders' out-degree (wavg)	0.059	0.059	0.043	0.000	0.024
	(0.005)	(0.006)	(0.007)	(0.007)	(0.006)
Borrowers' in-degree (wavg)	-0.044	-0.050	-0.048	-0.039	
	(0.003)	(0.003)	(0.003)	(0.003)	
Borrowers' out-degree (wavg)	0.024	0.032	0.035	0.018	
	(0.003)	(0.003)	(0.003)	(0.004)	
Pagerank					
Hub	-0.019	-0.003	-0.003	-0.014	-0.020
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Closeness	-0.009	-0.010	-0.008		
	(0.001)	(0.002)	(0.002)		
Out-weight HHI	-0.058	-0.075	-0.077	-0.057	-0.024
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)
In-weight HHI	-0.024	-0.019	-0.017	-0.004	-0.007
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
Equity share	-0.013	-0.046	-0.069	-0.054	-0.063
	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)
External assets share					
Size share		-0.068	-0.089	-0.098	-0.072
		(0.005)	(0.004)	(0.004)	(0.003)
Borrowers' self-borrowing share (wavg)	0.073	0.077	0.071	0.029	
	(0.003)	(0.003)	(0.003)	(0.003)	
Borrowers' borrowing share (wavg)				-0.009	0.004
				(0.004)	(0.001)
Lenders' equity (wavg)	0.044	0.026	0.010	0.002	
	(0.002)	(0.002)	(0.002)	(0.002)	
Borrowers' equity (wavg)	0.033	0.029	0.017	0.023	
	(0.002)	(0.002)	(0.002)	(0.002)	
Lenders' deposit share (wavg)	0.036	0.053	0.062	0.049	
	(0.002)	(0.003)	(0.003)	(0.003)	
ETH	0.212	0.209	0.159	0.265	0.160
	(0.010)	(0.011)	(0.011)	(0.013)	(0.008)
USDC	0.227	0.247	0.212	0.250	0.231
	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)
BTC	0.168	0.168	0.148	0.326	0.232
	(0.011)	(0.013)	(0.014)	(0.015)	(0.009)
$\mathbf{R^2}$	0.859	0.832	0.814	0.790	0.761
Adj. $\mathbf{R^2}$	0.859	0.831	0.813	0.789	0.761
F-statistic	2149.0	2135.0	1804.0	1173.0	1295.0
N obs	3980	4016	3816	3824	3824

Note: Each column reports the results of a separate OLS regression. The reference pool is DAI. Blank entries indicate variables not selected by the Lasso procedure. Robust standard errors are used to control for heteroskedasticity.