A Network Model of Wealth Inequality and Financial Instability

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Abstract

We propose a theoretical network model for understanding the relationship between wealth inequality and financial instability. Financial assets link individuals to form a network. Its topology varies with the level of wealth inequality or total wealth and determines network stability in the event of a negative income shock. Simulations demonstrate that increasing wealth inequality, measured by the skewness of the financial network's degree distribution, makes a wealthy network less stable, measured by the share of individuals failing financially. Aggregate wealth also has an inverted U-shaped effect on the model's network stability. Implications of the theoretical model are tested empirically on long-run panel data for nine countries with a reduced form, two-way fixed effects model. Estimates suggest that increasing wealth inequality, in an economy with high levels of aggregate wealth as measured by the wealth-income ratio, significantly increases the likelihood of financial crises, particularly stock market crashes. We find little evidence of an inverted U relationship between aggregate wealth and instability. These results suggest an important role for the distribution of accumulated assets in macro-financial stability.

Keywords: Wealth inequality, income inequality, financial crisis, growth and fluctuations, financial network, degree distribution.

JEL-Classification: D31, G01, L14, N10

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1 Introduction

Familiar plots from Thomas Piketty and Emmanuel Saez[1] display the share of income held by top percentiles in the US provocatively peaking before both the Great Crash and the more recent global financial crisis. This correlation raises important questions: Is inequality a destabilizing economic force? Or, is it, along with financial fragility, a symptom of deeper economic perturbations? The objective of this paper is to understand the relationship between wealth inequality and macroeconomic instability as manifested through the financial sector. Our approach is to think about two identical economies that are observed at a point in time and distinguished only by their distributions of wealth. We then ask, which is more unstable in the event of a negative income shock? To answer, we first construct an interpersonal financial network model using elements of graph theory. The model is then simulated, generating predictions as to the endogenous role of wealth distributions on financial stability. An empirical panel analysis is then carried out to test the theoretical model's implications.

We construct a theoretical model that provides a direct channel between top wealth inequality and the vulnerability of a financial network in the event of a shock. Financial assets represent a claim on some future cash flow. If that cash flow is generated by another individual's labor income, as we assume in our model, an individual owning a financial asset is naturally linked to the individual whose income generates the cash flow. The flows of a financial network, across these links, are what Hyman Minsky called a "complex system of money in/money out transactions."[2] Kregel (2014) makes the point that only a "slight disturbance" in money flows is necessary to cause instability and "widespread financial distress." This paper investigates if inequality helps determine the level of distress.

Wealth, as a collection of financial assets, by definition creates financial linkages in a network economy, where nodes represent households or individuals. The number of links connected to a single node equals its *degree*. Wealth inequality therefore enters the model via a network's degree distribution. As the distribution of wealth changes, the distribution of linkages in the network

[1]Their seminal paper on US income inequality, Piketty & Saez (2003), has since been continuously updated with new data. See also summary articles Piketty & Saez (2006), Atkinson et al. (2011), Alvaredo et al. (2013), and Piketty & Saez (2014).

[2]See (Minsky, 1986a, p. 69).

changes, thereby altering the topology of our interpersonal financial network and its stability, measured by the share of individuals whose net worth drops below a predetermined threshold, in the event of a random income shock. Contagion occurs because an income shock decreases net worth, triggering financial failure and accompanying costs that wipe out collateral wealth. The network structure implies wealth is dependent on the wealth of others, and so decreases in net worth spread. Simulations reveal two results: First, contagion, and thus instability, increases significantly when wealth and assets are unequally distributed in a wealthy network. Second, an inverted U-shaped relationship exists between aggregate network wealth and instability.

The model embeds several features of Minsky's Financial Instability Hypothesis—a framework that generates endogenous instability in a financial economy of connected banks and firms rather than individuals.[3] The key tenets incorporated are: interrelated balance sheets of individuals, where one's asset is always another's liability; assets/liabilities as commitments to future cash flows; a collapse in asset values stifling future cash flows; and a growing financial economy increasing the scale of contagion.

Of course our model is a gross simplification of a financial capitalist economy. We assume a static network, with one type of financial asset serviced by (uniform) labor income cash flows and individual net worth acting as collateral. But by stripping away the layer of financial intermediaries, it becomes possible to expose the latent relationships between individual creditors and debtors and to understand how the interpersonal distribution of financial assets in the economy may impact its overall stability.

Though our configuration also ignores network formation and other dynamics, it provides a tractable model that can be simulated and whose results are generalizable. To our knowledge, the only existing network models of wealth inequality are Lee & Kim (2007) and Kim et al. (2008), who also approximate it using the network's degree distribution. Neither considers contagion or network instability as this paper does.

Financial network models are frequently used, however, to model financial crisis. Battiston et al. (2012) pay particular attention to financial-accelerator dynamics in spreading contagion and also

[3]See Minsky (1975) and Minsky (1986b) for longer expositions, or Minsky (1992) for a brief summary.

consider diversified portfolios, whereas we consider a simple static economy with a single financial asset. Our attention is also focused on the effects of the distribution of this one asset on contagion. Glasserman & Young (2015) abandon topology measures (which our model features) in favor of bank-specific sufficient statistics to evaluate bank network contagion risks. They conclude that factors beyond pure spillovers such as confidence in counterparties and bankruptcy costs (which our model includes) are responsible for substantial economic losses from contagion. As in our model, Acemoglu et al. (2015) stress network structure as the determining factor in contagion, but they largely look at the magnitude and frequency of negative shocks to the network in order to analyze its stability whereas we explicitly vary the network topology. Each of the aforementioned models is derived from Eisenberg & Noe (2001), a network model of equilibrium clearing payments among banks, which is then shocked to measure network contagion.

A more nuanced finding in the financial network models literature is the nonmonotonic effect of connectivity on contagion. Increases in interdependence initially increase contagion and spillovers, but after a certain threshold, the increased linkages create a more robust financial system (Nier et al. (2007), Elliott et al. (2014a)). Gai & Kapadia (2010) characterize this nonmonotonicity as a "robust-yet-fragile" trait of financial markets, something our own model reflects.

While the financial network and crisis literature has not considered the role of inequality, the inequality literature has considered financial crises. In a qualitative survey of 84 crises across 21 countries over the past century, Morelli & Atkinson (2015) examine both the level of and changes in income inequality preceding a crisis episode. They conclude that the impact of either on financial crises is ambiguous.

A dynamic stochastic general equilibrium model by Kumhof et al. (2015)[4] is conceived, like our model, around assets linking households, in this case the top 5% to the bottom 95%. The authors demonstrate that a sequence of increasing income inequality (from exogenous income distribution shocks and weakened bargaining positions), rising household debt of the bottom 95%, and increasing financial assets of the top 5% causes higher leverage and a higher probability of crisis.

Rajan (2011) argues increasing US income inequality was but one critical "fault line" in the

[4] Kumhof et al. (2015) is the final published version of an IMF Working paper originally circulated in 2010 as Kumhof & Ranciere (2010).

crisis because it prompted an organized policy response of subsidized housing and mortgage market deregulation. Lax regulation not only increased homeownership but also led to destabilizing increases in credit. Testing the Rajan hypothesis, Bordo & Meissner (2012) regress changes in real credit growth on lagged changes in top income shares. They find no effect amongst a panel of 14 countries between 1870 and 2010, and conclude no link between inequality and crisis exists. Gu & Huang (2014) dissect their econometric methods and argue income inequality, in Anglo-Saxon countries, *does* determine credit growth—and therefore leads to financial crisis.[5] Evidence surveyed by van Treeck (2014) supports Rajan's hypothesis, but the relative income hypothesis is underscored to explain observed household saving behavior.[6] Stiglitz (2012) instead stresses a Keynesian mechanism: the marginal propensity to consume. Increasing income inequality decreases aggregate demand because wealthy households consume less willingly at the margin than poor households. The policy reaction is also loose credit.[7]

In the inequality literature cited above, the most common mechanism linking inequality to instability is household debt, measured as a debt-income ratio. Mason & Jayadev (2014) show that a set of so-called "Fisher dynamics" (i.e. interest rate changes, inflation, and income growth) account for most, if not all, of the increase in US household leverage since 1980—the same structural lever modeled by Kumhof et al. (2015). In other words, increasing household debt-income ratios do not necessarily imply newly issued debt (and new debt is the critical vehicle of the inequality-household debt-instability story). It provides an opening for a new mechanism: the specific network configuration as determined by the wealth distribution.

The implications of our model—which eschews the household debt mechanism in favor of a network topology story—are tested using a reduced form linear probability model and panel data from nine industrialized economies over the last century. We find strong statistical evidence that, in an economy with high levels of aggregate wealth, increasing top wealth shares significantly increases the likelihood of financial crisis, particularly a stock market crash—or a concurrent stock market crash and banking crisis. Our results hold when controlling for financial sector development, private

[5]Klein (2015) finds comovement between inequality and household debt using panel cointegration techniques, and Hauner (2013) finds a cointegrating relation in the US between income inequality and financial sector size.

[6]Elucidated in Duesenberry (1949), the relative income hypothesis posits individual saving is an increasing function of one's position in the income distribution relative to a local reference group and also one's past income.

[7]The central bank lowered interest rates and regulators pulled back, both setting the stage for a financial bubble and eventual collapse.

sector credit, top marginal tax rates, average rates of return, and GDP growth. Furthermore, no such relationships are found when income inequality replaces wealth inequality in our model. We do not find empirical support in favor of the inverted U-shaped relationship between aggregate network wealth and instability though. The empirical results suggest that our financial wealth network model is one tenable framework for describing the inequality-financial instability relationship.

The rest of the paper is organized as follows: Section 2 derives the theoretical financial network model, presents its mechanics, and introduces concepts of instability. Financial network parameter estimates are shared in Section 3, to motivate model calibration. Section 4 describes the method of quantitative simulation of random static networks also presents simulation results, including the important finding that increasing wealth inequality is destabilizing in wealthy networks. We derive no explicit analytical results from our model, thus Section 5 outlines an econometric reduced form model to empirically test the relationships revealed in simulations. Data and sources are described in Section 6 and the empirical results in Section 7. Since our empirical emphasis is on the marginal effects of a linear probability model, Section 8 evaluates robustness checks with logit estimators. We conclude in Section 9 and suggest extensions for further research.

2 Financial Network Model

In this section we introduce the wealth inequality network model, building off of Elliott et al. (2014a). Our model notably disregards financial intermediaries and instead relies on the latent financial links between asset and liability holders to form an interpersonal financial network economy. This enables a more tractable model between the economy's wealth distribution, how it translates to the network topology, and overall financial (in)stability.

2.1 Setup and Financial Assets

We consider a static financial network composed of nodes $i = 1, \ldots, n \in N$ where each node represents wealth owning individuals or households. (The terms node or individual are used interchangeably throughout.) We exclude firms, banks, and other types of organizations to simplify our model and to argue that variations in the distribution of wealth between individuals have network consequences.[8]

Links, or edges, connect two nodes and represent a financial claim between them. A financial asset is simply a claim on future cash flows. The links between all nodes in our network can be represented by an $n \times n$ matrix $\mathbf{G}$, called an *adjacency matrix*, with binary entries where $G_{ij} = 1$ if node i has some financial claim on node j and 0 otherwise. Claims are directional, implying an asset position for i and a liability for j and a direction of future cash flows from j to i. Matrix $\mathbf{G}$ is thus composed of creditors (rows) making financial claims on debtors (columns). Though individuals are along both dimensions of the matrix, financial claims need not be reciprocated—and $\mathbf{G}$ need not be symmetric. Our network can be summarized as an unweighted directed graph $\mathcal{G}(N, G)$ whose edges indicate the existence, and paths, of financial flows between individuals.

Assume there exists only one type of financial asset held by individuals and households, a type of asset-backed security. Each security is a claim on future labor income cash flows generated by the liability holder, with their net worth serving as collateral.[9] A node i owns d_i financial assets, where $d_i = \sum_j G_{ij}$ is called the node's *in-degree*. This also represents the total number of individuals i holds claims against (a row sum in $\mathbf{G}$). A financial asset-owning node may also back the value of an asset themselves, a function of their own valuation. Let d_j^{out} represent the total number of financial liabilities node j is collateralizing, where $d_j^{out} = \sum_i G_{ij}$ (a column sum in $\mathbf{G}$). Called the *out-degree*, d_j^{out} represents the number of financial outflows from individual j to claimant nodes. Financial assets are distributed according to some probability distribution $f(d_i)$ called the *degree distribution*.[10] Only some fraction $c \in (0, 1)$ of each individual's overall net worth is collateralized and can be claimed by, and owed to, other individuals holding financial assets within the network.

We define a matrix $\mathbf{C}$ to describe the relative ownership claims on each node's value in the network. This *cross-holdings matrix* has, for $i \neq j$, element

[8]To be sure, many individuals rely on opaque institutions and organizations to hide private wealth. See Zucman (2014) and Zucman (2015) for a detailed analysis on hidden private wealth.

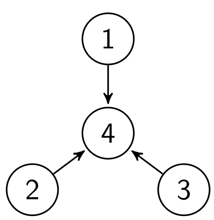
[9]Node net worth is discussed in detail in Section 2.3.

[10]Note that $\sum d_i = \sum d_j^{out}$ so that total assets equal total liabilities and the economy's balance sheet balances.

$$C_{ij} = \begin{cases} c\frac{G_{ij}}{d_j^{out}} & \text{if } d_j^{out} > 0 \\ 0 & \text{else.} \end{cases} \tag{1}$$

Our unweighted adjacency matrix $\mathbf{G}$ has become a weighted matrix $\mathbf{C}$ of financial claims between nodes, where element C_{ij} is the share of individual j's future cash flows, backed by their net worth, claimed by i. The total number of asset holders d_j^{out} holding assets backed by individual's j's wealth are each entitled to an equal portion of future cash flows. Node cash flows not claimed by other individuals $(1-c)$ are saved. (Savings do not accumulate as our model is static.) The savings of each node are summarized in a diagonal matrix $\hat{\mathbf{C}}$, with element $\hat{C}_{jj} = 1 - \sum_i C_{ij}$. From this definition we can also rewrite the total sum of claims made on individual j as $\sum_i C_{ij} = 1 - \hat{C}_{jj}$.

To illustrate, consider the network in Figure 1a, where $n = 4$ and $c = 0.5$. The corresponding adjacency and cross-holdings matrices are in Figure 1b. Notice, from $\mathbf{G}$'s bottom row, that node 4 has financial assets which are claims on the cash flows of nodes 1, 2 and 3, but has no cash flow obligations itself, and thus an in-degree $d_4 = 3$ but an out-degree $d_4^{out} = 0$. Because $c = 0.5$, 50 percent of nodes 1, 2, and 3's future incomes flow to node 4, seen in the last row of $\mathbf{C}$.



(a) Graph of network

$$\mathbf{G} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 \end{bmatrix}, \mathbf{C} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ .5 & .5 & .5 & 0 \end{bmatrix}$$

(b) Corresponding adjacency and cross-holdings matrices.

Figure 1: Example of a four-node network

2.1.1 Microfoundations

Consider one possible microfoundation for our network model thus far. Suppose our static network is an endowment economy, whereby all nodes are endowed with a single type of financial asset—like our asset-backed security. The endowments are randomly distributed between nodes according to some probability distribution $f(d_i)$, where d_i is the total number of financial assets node i owns. Which nodes then back each of the d_i securities node i owns is randomly determined.

A richer form of heterogeneity could allow for variation amongst nodes rather than endowments. Let ρ represent a symmetrically distributed stochastic discount factor where $\rho \in \{\rho_l, \rho_\mu, \rho_h\}$.[11] If a node is assigned the lower discount factor ρ_l, then the node must borrow to consume single good y as they have a preference for consumption. In this circumstance $d_l < d_l^{out}$ and the individual is a net debtor. If a node receives the higher discount factor ρ_h it is a lender with a preference for accumulating assets. In this event $d_h > d_h^{out}$ and the individual is a net creditor. Should the node receive the mean discount factor ρ_μ, then $d_\mu = d_\mu^{out}$.

Another possibility is to consider an economy of entrepreneurs. Each node is endowed with some productive asset and an intermediary good, drawn from a distribution. The intermediary good may be consumed, but nodes prefer to consume a final consumption good that requires the interaction of at least two intermediary goods. Credit, fixed in aggregate, is extended between entrepreneurs to produce the final consumption good, which may be used to repay liabilities.

2.2 Real Assets

In addition to the financial asset, there exist $k = \{1, \ldots, m\} \in M$ real, or physical, assets in the network. Think of productive assets like land or human capital. A matrix $\mathbf{D}$, describing the pattern of real asset claims and analogous to the cross-holdings matrix $\mathbf{C}$, is composed of elements D_{ik}, which denote individual i's share of real asset k . We can now describe the *gross value* of individual i's total assets V_i as the sum of their real asset claims (each at their respective prevailing market price, p_k) and financial asset claims (backed by the liability holder's own gross value).

$$V_i = \sum_k D_{ik} p_k + \sum_j C_{ij} V_j. \tag{2}$$

Written in matrix notation, we have $\mathbf{V} = \mathbf{Dp} + \mathbf{CV}$, and solving for the gross value of each individual in the network yields a vector of values $\mathbf{V}$, where

$$\mathbf{V} = (\mathbf{I} - \mathbf{C})^{-1}\mathbf{Dp}. \tag{3}$$

[11] In Krusell & Smith (1998), a dynamic general equilibrium model using stochastic discount factors generates a Pareto wealth distribution in the tails that closely fits the empirical estimates of Wolff (1994).

Note, however, that the gross value of individual i's total assets V_i double counts real asset claims D_{ik}. They appear not only in the first term of Equation (2) but also in the second term as a component of other individuals' own valuations V_j. Therefore, in the next section, we derive a measurement of node net worth.

We simplify our model by assuming there exists one type of real asset, human capital, with $m = n$ different units. Because the only real asset in this economy is human capital, it cannot be owned by anyone else, though others may have claim to the future cash flows generated by it.[12] In other words, each node in the network is endowed with one unit of labor that is inelastically supplied. Output is generated by a linear production function with labor or human capital as the only argument, $y = l$ where $l \equiv D_{ii}$. Because human capital, or labor, is owned entirely by the individual endowed with it, we let $\mathbf{D} = \mathbf{I}_n$. Human capital prices are homogeneous and normalized to one, such that $p_k = 1 \ \forall \ k$. Total output in this static economy is equal to the sum of real assets made into commodities, or total human capital:

$$Y = \sum_{i=1}^{n} y = \operatorname{Tr} \mathbf{D} = m = n. \tag{4}$$

Because real assets are homogeneous in our network, the model is designed to specifically study how the distribution of financial assets $f(d_i)$ impacts the network's overall stability.

2.3 Net Worth

A node's net worth is defined as total assets (real and financial) less liabilities.[13] To derive an expression, we sum real assets and ownership claims on other individuals' wealth (inflows) and subtract claims on one's own wealth (outflows):

$$v_i = \sum_k D_{ik} p_k + \sum_{j \neq i} C_{ij} V_j - \left(\sum_{j \neq i} C_{ji} \right) V_i. \tag{5}$$

[12] Allowing $\mathbf{D}$ to represent human capital takes into consideration a common critique of Piketty (2014), best articulated by Blume & Durlauf (2015), that aggregating financial and physical assets at prevailing market prices crucially ignores the important contemporary role human capital plays in generating cash flows.

[13] See, for example, Davies & Shorrocks (1999) and Davies et al. (2007). In Elliott et al. (2014a) this is also called a node's *market value*, since their model's nodes represent firms or banks.

Note that the first two terms are simply individual i's gross value, or the sum of real and financial assets defined in Equation (2). From this we subtract total liabilities. In matrix form we have,

$$\mathbf{v} = \mathbf{Dp} + \mathbf{CV} - (\mathbf{I} - \hat{\mathbf{C}})\mathbf{V} = \mathbf{Dp} + [\mathbf{C} - (\mathbf{I} - \hat{\mathbf{C}})]\mathbf{V}$$

where $\mathbf{I} - \hat{\mathbf{C}}$ is a diagonal matrix representing weighted total obligations in the network and $\mathbf{C}$ represents weighted total claims. Substituting the gross value from Equation (3) for $\mathbf{V}$ and rearranging leads to a unique interpretation of net worth.

$$\begin{aligned}
\mathbf{v} &= \mathbf{Dp} + [\mathbf{C} - (\mathbf{I} - \hat{\mathbf{C}})]\mathbf{V} \\
&= \mathbf{Dp} + [\mathbf{C} - (\mathbf{I} - \hat{\mathbf{C}})][(\mathbf{I} - \mathbf{C})^{-\mathbf{1}}\mathbf{Dp}] \\
&= ((\mathbf{I} - \mathbf{C}) + \mathbf{C} - \mathbf{I} + \hat{\mathbf{C}})(\mathbf{I} - \mathbf{C})^{-\mathbf{1}}\mathbf{Dp} \\
\mathbf{v} &= \hat{\mathbf{C}}(\mathbf{I} - \mathbf{C})^{-\mathbf{1}}\mathbf{Dp} \\
\mathbf{v} &= \mathbf{ADp} \qquad (6)
\end{aligned}$$

Net worth can now be derived from the overall claims between all nodes in the network (matrix $\mathbf{A}$) made on the underlying real assets (matrix $\mathbf{D}$ at price $\mathbf{p}$) of the economy. Since each real asset represents a node's human capital, net worth is simply derived from the cumulative claims on future output generated by another's human capital.

The utility of introducing matrix $\mathbf{A} = \hat{\mathbf{C}}(\mathbf{I} - \mathbf{C})^{-\mathbf{1}}$, called the *dependency matrix*, is that it summarizes the total claims between all nodes, i.e. the sum of direct and indirect dependencies between individuals in the network.[14] It is possible for element A_{ij} to be nonzero even if the corresponding element in the cross-holdings matrix, C_{ij}, is zero—an indication of indirect claims by i on j via other nodes in the network but no direct claims. The dependency matrix $\mathbf{A}$ is not unlike Leontief's input-output matrix, Elliott et al. (2014a) posit, in its ability to summarize the interconnections of a network economy. It is instructive to examine the differences between direct holdings (from cross-holdings matrix $\mathbf{C}$) and total direct and indirect holdings (from dependency matrix $\mathbf{A}$) in the examples in Section 2.6.

[14] Matrix $\mathbf{A}$ has all nonnegative elements and is also column-stochastic, thus each of its columns sums to 1 ($\sum_i A_{ij} = 1$).

The dependency matrix also simplifies the accounting considerably. Claims on individual real assets, rather than both financial assets and liabilities, become a sufficient statistic to determine an individual's overall net worth when calculating the impacts of a shock as they reverberate through the network. In fact, all wealth is derived from human capital.

Given that we can calculate the net worth of an individual v_i using Equation (2.3), why not directly model the wealth distribution with $f(v_i)$? Using $f(v_i)$, rather than $f(d_i)$, to model wealth inequality obscures the critical role that interconnectedness plays in the financial network. It is precisely the connecting structure of the network that determines whether or not a shock causes contagion. In order to have a tractable link structure in our adjacency matrix the random network's inequality must be derived from the degree distribution, $f(d_i)$. Finally, the degree distribution of the network characterizes the same magnitude of wealth inequality given by the distribution of individual net worths, without loss of generality.

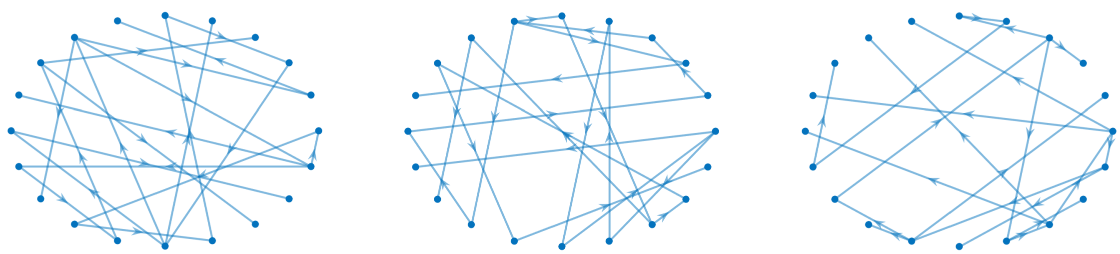
2.4 Wealth Inequality

The wealth distribution of the network can be decomposed into its real and financial components. We have already assumed real assets, in the form of human capital, are fixed and equal for all individuals. Financial assets, then, entirely determine the wealth distribution, defined by the degree distribution of financial assets $f(d_i)$. Wealthier individuals have more positive financial claims and links to other individuals in the network than less wealthy individuals. A deterministic degree distribution, for example, captures perfect equality of financial wealth. Let a Pareto distribution describe the degree distribution of an unequal society where the probability of someone having d_i financial assets is given by $p(d_i) = ad_i^{-\gamma}$, with $\gamma > 0$.[15]

The aggregate financial wealth of the entire network is equal to total number of financial claims $\sum d_i$. Because our network is static and the number of individuals n remains fixed, increasing the number of assets in the network increases total financial wealth. This is akin to the economy growing through increased credit, or financialization at the extensive margin.

The graphs in Figure 2 illustrate how a random network's structure changes with financial wealth

[15] Our network model simulation results are robust to allowing wealth inequality to be determined by the out-degree distribution $f(d_i^{out})$ rather than the in-degree distribution $f(d_i)$.



(a) $\gamma = 2.35$ **(b)** $\gamma = 1.65$ **(c)** $\gamma = 1.025$

Figure 2: Random network graphs ($n = 20$)

inequality via the Pareto parameter γ. Each network with $n = 20$ and expected in-degree $E[d_i] = 1$ is generated randomly for a specified γ. The highest Pareto parameter ($\gamma = 2.35$) corresponds to the lowest inequality among the three graphs. Its financial claims are more evenly spread out compared to the most unequal random network graph ($\gamma = 1.025$).[16]

2.5 Shocks, Financial Failure, and Contagion

Though our model is static, contagion is evaluated dynamically. We therefore introduce a time subscript to specify periods in relation to the initial shock in period $t = 0$.

Recall that, initial real asset prices are set to 1 so that $\mathbf{p}$ is a vector of ones. A random exogenous income shock at time $t = 0$ impacts one individual's net worth through their real asset price, such that $p_i = 1$ becomes $\tilde{p}_i = \lambda p_i = \lambda \; \forall \; t \geqslant 1$, where $\lambda \in [0, 1)$. The magnitude of the negative real asset price shock $\tilde{p}_i$ is decreasing in λ. All other individuals in the network experience no real asset price shock at $t = 0$, and thus the vector of real asset prices after the initial shock $\tilde{\mathbf{p}}$ contains a value λ in the i^{th} row and 1 everywhere else.[17] Because there exists a uniform risk ($\frac{1}{n}$) of shock, no risk premia are priced into financial assets.

The negative shock to an individual's financial wealth, transmitted through an exogenous price drop in their human capital, could represent the loss of a job or earning capacity. If, as a result of

[16]Each graph is generated thusly: draw a random Pareto distribution of financial claims d_i, truncated at the top to ensure $E[d_i] = 1$ across distributions; randomly link financial claims d_i to other nodes to create adjacency matrix $\mathbf{G}$; plot directed graph $\mathbf{G}$.

[17]One could consider the notation $\tilde{\mathbf{p}}_i$ to indicate that individual i experiences the negative shock.

this income shock, the individual's wealth $v_{i,t}$ should fall below some threshold $\underline{v}_i$ they experience *financial failure*. Network instability is defined by the accumulation of many individuals failing financially. Financial failure triggers bankruptcy costs β_i. They are not to be taken literally (net worth remains positive), but instead as representative of increased financial burdens faced when an individual's net worth is depressed by some relative amount. Such burdens could include direct costs like attorney and accounting fees as well as indirect costs such as lost income, increased future borrowing costs, loss of collateral or counterparty confidence. We denote this as $\beta_i(\tilde{\mathbf{p}})I_{v_{i,t}<\underline{v}_i}$, where I is an indicator function taking a value of 1 if $v_{i,t} < \underline{v}_i$ and 0 otherwise.

We assume that $\underline{v}_i = \theta v_i > 0$, with $\theta \in (0,1)$ remaining constant throughout the dynamic contagion process. Parameter θ describes individual financial fragility. A high θ implies a more easily breached valuation threshold and likelier financial failure in the event of a shock, whereas a low value means more robust personal finances. The failure threshold $\underline{v}_i$ remains positive because financial duress and accompanying cash flow strains need not imply negative net worth in our model, only a financial setback such that creditors are not repaid and penalties imposed.[18]

Let $\mathbf{b}_{t-1}$ represent a vector of failure costs with element $b_{i,t-1} = \beta_i(\tilde{\mathbf{p}})I_{v_{i,t-1}<\underline{v}_i}$. By definition, $\beta_i = 0 \; \forall \; i$ at $t = 1$ because no individuals have failed yet. The first iteration of calculating new node valuations occurs at $t = 1$,[19] so equation (2.3) is rewritten to incorporate failure costs:

$$\mathbf{v_t} = \hat{\mathbf{C}}(\mathbf{I} - \mathbf{C})^{-\mathbf{1}}(\mathbf{D}\tilde{\mathbf{p}} - \mathbf{b_{t-1}}) = \mathbf{A}(\mathbf{D}\tilde{\mathbf{p}} - \mathbf{b_{t-1}}) \text{ for } t = 1, \ldots, T. \tag{7}$$

The dependency matrix $\mathbf{A}$ not only describes the share of an individual's wealth owed to claimants, but also the failure costs absorbed by those same claimants in the event of an individual's financial failure. This is the source of contagion. When an individual fails financially their remaining net worth (collateral) is wiped out from failure costs—we assume $\beta_{i,t} = v_{i,t}$ in our calibration in Section 4.2. The failure costs spread according to the dependency matrix $\mathbf{A}$.

Consider the following example of dynamic contagion (illustrated in Figure 3). Suppose some individual j is the first financial failure as a consequence of receiving human capital price shock

[18] If $\underline{v}_i \leqslant 0$, it would imply individual human capital value is 0 or negative, an unrealistic scenario.

[19] An algorithm in Appendix Section A.1 describes the process of iteratively calculating node valuations in the event of a negative shock in order to determine the number of total financial failures resulting from the initial shock.

$\tilde{p}_j = \lambda$ at time $t = 0$, such that $v_{j,1} < \underline{v}_j = \theta v_j$ in the first re-evaluation at $t = 1$. This prompts failure costs $\beta_{j,1}$ which deplete collateral wealth and are partially absorbed by, for example, individual i's dependency on j as represented by a nonzero value for element A_{ij} in the dependency matrix. Such codependence implies i's value decreases by the amount $A_{ij}\beta_{j,1}$ in period $t = 2$. Should i's value $v_{i,2}$ fall below $\underline{v}_i$, it would incur its own failure cost $\beta_{i,2}$ and as a consequence alter the values, in period $t = 3$, of all individuals i is financially connected to (directly or indirectly) through the dependency matrix $\mathbf{A}$.

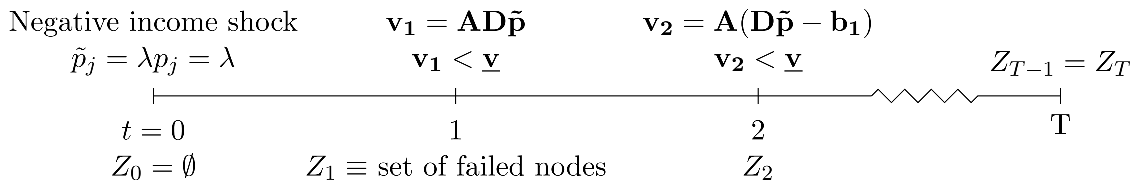


Figure 3: Timeline of Network Contagion

A static financial network gives way to a dynamic process of cascading failures. The instability is initiated by a decrease in one individual's earning capacity and wealth, hindering their ability to service financial debts and thus provide cash flows for the financial claims creditors have on their output.[20] This cessation of cash outflows to creditors decreases each creditor's wealth, setting off progressive failures as any decline in a creditor's wealth below their own failure threshold would cause additional failure costs.

Any shock to individual net worth could initiate contagion. Because our network's wealth is ultimately derived from human capital, it is the intuitive income source to receive the shock. The model also emphasizes the role of network topology on instability by shocking only individual labor income rather than all labor income, which could cause instability because of the scope of the shock and not necessarily network structure.

A simple algorithm to identify the set of nodes failing is outlined in Section A.1 of the Appendix. Each iteration of the algorithm represents one period t and appends another group of individuals, Z_t, who fail as a direct result of the preceding $t-1$ group's failures. Contagion stops when no new individuals in the network fail.

[20] This appropriates Minsky's position on financial instability: "the behavior and particularly the stability of the economy change as the relation of payment commitments to the funds available for payments changes and the complexity of financial arrangements evolve." (Minsky, 1986a, p. 197)

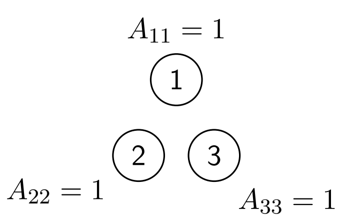
2.5.1 From Contagion to Crisis

We define the level of network instability as proportional to the share of individuals in the network who have failed financially $S = \frac{|Z_T|}{n}$. A financial crisis could be said to manifest when a sufficient share of the network fails financially, though we are agnostic about a specific threshold. Network failure in our model is driven by drops in the value of initially real, but then financial, assets. This is congruent with empirical definitions of financial crisis, which may specify the magnitude asset values must drop. When describing instability in the context of empirical results in Section 7, we refer to an increase in the likelihood of crisis.

2.6 Example

We present one example of a simple network with $n = 3$ nodes and increasing numbers of financial assets to help elucidate concepts from the model. The example is illustrative of the network and matrix structures, not contagion effects.[21] Throughout, we assume $\mathbf{D} = \mathbf{I}_3$ and $p_k = 1 \ \forall \ k$.

First, consider an unconnected network. No edges linking any nodes exist (Figure 4a). In a network with no financial claims, each individual keeps all future cash flows and their net worth depends only on their human capital—which is homogeneous. When a shock occurs, only the wealth of the individual experiencing the shock declines, but every other node is isolated. No contagion can occur. (Adjacency matrix **G** is omitted from Figure 4b because, like **C**, it is all zeros.)



(a) Graph of network

$$\mathbf{C} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \mathbf{A} = \hat{\mathbf{C}}(\mathbf{I} - \mathbf{C})^{-1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

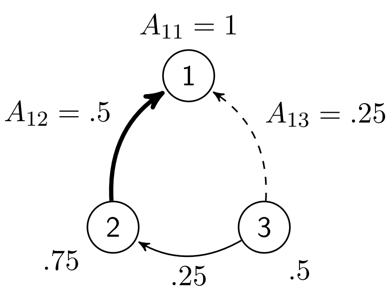
(b) Corresponding cross-holdings and dependency matrices

Figure 4: Three-node network with no financial assets

Now, suppose two financial assets are introduced into our network (see Figure 5). The total share of a node's net worth that may be claimed by other nodes, c, is 0.5. All elements in the

[21]Because this is the smallest possible network that can display a variety of link structures, a shock to any connected node may or may not immediately cause failure for all nodes.

diagonal savings matrix $\hat{\mathbf{C}}$ will be 1, unless financial claims are made on a node's value and it equals 0.5. The network's two financial assets represent two claims: node 1 has a claim on node 2's future cash flows and node 2 has a claim on node 3's. Therefore $d_1 = d_2 = 1 = d_2^{out} = d_3^{out}$ while $d_3 = 0 = d_1^{out}$. According to Equation (1), $C_{12} = 0.5$. Node 1, therefore, has claim to half of node 2's cashflows while node 2 retains the other half. The same relationship holds between nodes 2 and 3, where $C_{2,3} = 0.5$. Importantly, nodes 1 and 3 are indirectly connected through node 2 even though no direct link exists. (Note the dashed edge in Figure 5a.) Hence $A_{13} = 0.25 > C_{13} = 0$, because node 2 claims half of node 3's net worth, and node 1 claims half of 2's. Node 1 also has the highest net worth ($A_{11} = 1.75$) of which 0.75 is derived from the other two nodes. Node 2 has a net worth of 0.75, of which 0.25 is derived from node 3, and node 3 has no financial assets and thus a net worth of only 0.5 (equal to its own savings). A shock to node 1 would have no effect on the other nodes since no other nodes have financial claims on node 1 or are dependent on node 1's net worth. Only if nodes 2 or 3 were shocked could multiple nodes fail (nodes 1 and 2) since others are dependent on them.



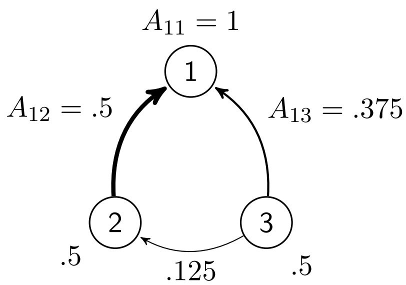
(a) Graph of network

$$\mathbf{C} = \begin{bmatrix} 0 & .5 & 0 \\ 0 & 0 & .5 \\ 0 & 0 & 0 \end{bmatrix}, \mathbf{A} = \hat{\mathbf{C}}(\mathbf{I} - \mathbf{C})^{-1} = \begin{bmatrix} 1 & .5 & .25 \\ 0 & .5 & .25 \\ 0 & 0 & .5 \end{bmatrix}$$

(b) Corresponding cross-holdings and dependency matrices

Figure 5: THREE-NODE NETWORK WITH TWO FINANCIAL ASSETS

Next, we introduce another asset into the network giving a total of three financial assets in the network. (See Figure 6.) Node 1 gains an explicit financial claim on node 3. The in-degree of each node is now $d_1 = 2, d_2 = 1, d_3 = 0$. Of the 0.5 share of node 3's value that is securitized within the network, half goes to node 2 and the other half to node 1. But because node 1 has a claim on node 2's value, it also indirectly receives cash flows from node 3 via node 2 as well. Thus its indirect total cash inflows from node 3 are greater than its direct cash flows, or $A_{13} = 0.375 > C_{13} = 0.25$. In this graph with three financial assets, contagion depends on which individual is initially shocked. For example, if $\lambda = 0$ and node 1 were shocked (such that $\tilde{p}_1 = 0$), then only node 1 would fail



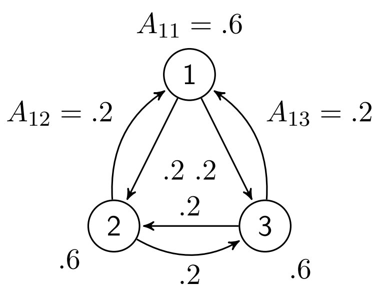
(a) Weighted network graph

$$\mathbf{C} = \begin{bmatrix} 0 & .5 & .25 \\ 0 & 0 & .25 \\ 0 & 0 & 0 \end{bmatrix}, \mathbf{A} = \begin{bmatrix} 1 & .5 & .375 \\ 0 & .5 & .125 \\ 0 & 0 & .5 \end{bmatrix}$$

(b) Corresponding cross-holdings and dependency matrices

Figure 6: Three-node network with three financial assets

financially. No other nodes depend on its value so its failure would not disrupt the net worth of others. If, on the other hand, node 3 were shocked (for the same λ) then because its value backs the financial assets held by the other nodes it would cause all three nodes to fail.



(a) Weighted network graph

$$\mathbf{C} = \begin{bmatrix} 0 & .25 & .25 \\ .25 & 0 & .25 \\ .25 & .25 & 0 \end{bmatrix}, \mathbf{A} = \begin{bmatrix} .6 & .2 & .2 \\ .2 & .6 & .2 \\ .2 & .2 & .6 \end{bmatrix}$$

(b) Corresponding cross-holdings and dependency matrices

Figure 7: Three-node network with maximum $(n-1)$ financial assets

Finally, suppose all nodes are linked such that $d_i = d_i^{out} = n - 1 \ \forall \ i$ (Figure 7). The network has absorbed the maximum possible number of financial assets $(n^2 - n)$ and represents a *complete graph*—a special case of a *regular graph* where all nodes have equal degree. Each node has equal net worth: 0.6 from oneself and 0.2 from each of the other two nodes. Since everyone is connected in both directions, any shock will precipitate contagion.

3 Empirics on Financial Networks

To motivate the choice of a Pareto distribution to model inequality of financial assets (and thus financial connections), in this section we first describe several empirical findings from the financial network literature on the connectivity of financial institutions through interbank lending as well as the distribution of those connections.[22] Then we present estimates fitting various datasets of individual wealth to Pareto (power-law) distributions along with their goodness of fit and tests against alternative distributions.

3.1 Interbanking Networks

In a seminal work, Furfine (1999) developed an algorithm to parse transactions data of the federal funds market for bilateral overnight lending.[23] Summarizing interbank lending market concentration during the first quarter of 1998, Furfine finds that the top 1% of financial institutions in the federal funds market account for two thirds of all assets. They also represent 86 percent of federal funds sold and 97 percent of federal funds bought. These levels of financial market concentration are within the range of parameter estimates we test in our simulations in the next section.

Empirical estimates of various financial network structural parameters from Blasques et al. (2015) are based on data from Dutch interbank markets between 2008 and 2011.[24] Amongst the top 50 lending banks, the authors estimate a mean in-/out- degree of 1.04, with standard deviations of 1.6 and 1.84, respectively. On average, banks lend to or borrow from an average of 1.04 different banks. At the same time, they find very positively skewed in-/out- degree distributions, supporting the Pareto distribution we impose on our model.

Bech & Atalay (2010) describe the topology of the federal funds market in the US between 1997 and 2006—also using Fedwire data and the Furfine (1999) algorithm. In 2006, banks had an average in-/out- degree of 3.3 ± 0.1 for overnight interbank lending.[25] Among many other parameters describing the topology of the federal funds market, they estimate the out-degree distribution for

[22] We must rely on existing research as only aggregate lending data are publicly available. Fedwire Funds Service, a large value transfer service operate by the Federal Reserve—though not unique to federal funds lending—provides bank-level data of the US federal funds market.

[23] All subsequent papers cited in this section rely on the Furfine (1999) algorithm, or adaptations of it, to generate their interbank lending data from the broader Fedwire data. An important caveat of the resulting Furfine interbank lending data are their dependence on transactions occurring through Federal Reserve balance sheets, but not the banks' own lending.

[24] Unlike the Fedwire data in Furfine (1999), the authors use TARGET2 interbank lending data (the Eurosystem equivalent of Fedwire) which specifies individual borrowing and lending institutions for indicated bilateral credit payments. The Dutch interbank lending data has also been cross-validated against Italian and Spanish interbank lending data to minimize type I errors.

[25] The authors define a directed link as going from lender to borrower. Thus their definition of a bank's out-degree corresponds to our own definition of an individual's in-degree (cash flows directed in towards the asset holder).

banks on a representative day in their sample period, concluding that a power-law distribution provides the best fit with a parameter estimate of 1.76 ± 0.02. Their results lend support to our model's degree distribution parameterization, described in Section 4.2.

The aforementioned papers only consider unsecured overnight interbank lending. Bargigli et al. (2015) study both secured and unsecured lending for varying maturities, reflecting our own model more closely—which posits financial assets are secured by an individual borrower's labor income and hence a longer maturity. The authors estimate the the in-/out- degree distributions of the Italian Interbank Network (IIN) between 2008 and 2012, and for 2012 they report power-law parameters on interval [1.8, 3.5]. A similar parameterization is applied in our model's Pareto degree distribution of individual financial assets. Their expected degrees of networks with long-term maturities are also within our range of mean degree values.

Though we abstract from financial intermediaries writ large, our interpersonal financial network framework emphasizes the latent interconnectedness of parties in a financial economy. Estimates on existing networks are therefore helpful guides for reasonable calibration.

3.2 Financial Distributions

The Pareto distribution, or power law, is typically used to estimate top shares.[26] Thus our model more accurately describes a network of top financial asset holders where we assume financial assets are Pareto distributed. According to the Survey of Consumer Finances (SCF), between 1989 and 2007 US households in the top 1% of households by net worth typically owned one third of all wealth, around 29 percent of all assets, and also nearly one third of all financial assets. The top 10% held nearly two thirds of all wealth and assets, and over 70 percent of all financial assets. The bottom 50%, however, never held more than 3 percent of financial assets or 6.7 percent of all assets (which almost entirely consisted of real estate). We argue that since top wealth holders describe the majority of financial assets, their network topology is a sufficient determinant of overall financial instability.

Given that the power-law relationship $p(x) = \Pr(X = x) = Cx^{-\gamma}$ implies $\ln p(x) = \mathit{constant} +$

[26] See Kennickell (2009) for estimates of the nonparametric wealth distribution in the US using Survey of Consumer Finances data and Vermeulen (2014) for a detailed discussion on estimating top tails in wealth distributions.

$\gamma \ln x$, the approximate linear relationship on a log-log plot suggests its absolute slope is a reasonable estimate of the parameter γ. Since Pareto (1896), power-law distributions have been traditionally estimated thusly: construct a histogram representing the frequency distribution of the variable x; plot on a log-log scale; finally, if approximately linear, estimate its slope to find the scaling parameter.[27]

For numerous reasons outlined in Clauset et al. (2009), the above estimation method is problematic. Instead the authors propose a maximum likelihood estimation method whereby the scaling parameter γ is estimated conditional on a correct estimate of the lower bound value for power-law behavior x_{min}—as chosen by Kolmogorov-Smirnov statistics. Following the methodology of Clauset et al. (2009) and applying it to the 1989 and 2010 Survey of Consumer Finances, we find a wide range of plausible power-law fittings for US household data on total net worth, financial assets, and total debt.[28] We repeat the exercise for comparable variables using three international datasets from the Luxembourg Wealth Study (LWS): the UK in 2007, and Australia and Italy in 2010. (Each country-year pair is an observation in our empirical analysis in Section 7.)

Results vary by country (Table 1). The US data are the least representative of a Pareto, or power-law, distribution. Though parameter estimates are easily fitted to the data, hypothesis testing rejects a statistically significant goodness of fit between generated data and fitted data.[29] The Pareto distribution fits US financial asset data from 1989 best, though only 60 percent of comparisons between generated and fitted data fail to reject the null that they come from the same Pareto distribution. In all other sets of US data we reject the null the majority of the time. However, we also reject any alternative distributions (the exponential and lognormal, both with and without cutoff values) as good fits of the US data.[30] Fitted Pareto parameters range from 1.450 (US net worth in 2010), indicating high inequality, to 2.208 (US financial assets in 1989), indicating much lower inequality.

Data for the UK, Australia and Italy consistently fit a Pareto distribution, across all household

[27] In Pareto (1896), $\hat{\gamma}$ was approximately 1.5—and conjectured to be fixed.

[28] Estimation programs are available online at http://tuvalu.santafe.edu/∼aaronc/powerlaws/.

[29] Generated data come from 2,500 randomly generated Pareto distributions simulated from our fitted parameter estimates.

[30] Using the R package `poweRlaw` , we also test against alternative poisson distributions for the US data. Using a Vuong test, also outlined in Clauset et al. (2009), we prefer a Pareto distribution against a poisson in all cases.

variables. In at least 87 percent of the comparisons between generated Pareto distributions and fitted Pareto distributions we cannot reject a difference between the two. Alternative distributions are also unanimously rejected as possible models. Though the Pareto is a uniformly good fit of the LWS data, the scaling parameter estimates are much higher than for the US data, with a minimum of only 2.224 (AUS financial assets in 2010) and a maximum of 3.571 (AUS liabilities in 2010). One reason why may be that each data series is measured in local currency units, so larger cutoff values of the power-law behaving region suggest a less skewed distribution (and higher scaling parameter) above it. Another reason could be over-sampling high-earning households in the SCF survey population.

A Pareto distribution estimates top wealth inequality in the tail of the distribution, thus our interpersonal financial network is representative of top financial asset holders and their influence on stability. Along with the empirical literature on interbank networks, our estimates of Pareto parameters for 15 different wealth series suggest that our range of calibrated γ values [1.025, 2.375], for the simulation in the proceeding section, are reasonable.

4 Simulation

4.1 Setup

In a static random network the number of nodes is fixed and links are established following some probabilistic rule. Let d_i be drawn independently from the Pareto distribution $p(d_i) = ad_i^{-\gamma}$, where γ is the Pareto, or power-law, parameter and a is a normalizing constant.[31] For example, suppose a random draw from the degree distribution yields an in-degree for individual i of 10. Ten financial assets are owned by i, each backed by the net worths of 10 different individuals. As a creditor, i is represented by a row in the adjacency matrix $\mathbf{G}$. Those 10 financial claims are randomly distributed to debtors, represented along columns, in $\mathbf{G}$, so long as $G_{ii} = 0$. In other words, the Pareto draw tells us the row sum of G_i, which is then randomly distributed in columns along row i.

If the expected in-degree of our network is $d = E[d_i]$, then, because our network size is fixed at

[31] Assuming a Pareto distribution only amongst top wealth holders is trivial since our simulated network includes $n = 100$ nodes and thus no distribution within the top 1%.

$n = 100$, any increase in aggregate wealth $\sum d_i$ directly increases d.

One characteristic of the Pareto distribution is that its scaling parameter γ decreases in the distribution's skewness. Therefore, it is a natural inequality measure for a Pareto distribution while also directly related to top percentile shares: if a random variable is Pareto distributed, then the share going to the top q percent of the population is equal to $S(q) = (\frac{100}{q})^{\frac{1-\gamma}{\gamma}}$. The Gini index can also be directly derived from the Pareto shape parameter with $GINI = (2\gamma - 1)^{-1}$ when $\gamma > \frac{1}{2}$. Each relationship illustrates that wealth inequality is decreasing in γ.

To understand the effects of the network's aggregate financial assets $\sum d_i$ and wealth inequality $\frac{1}{\gamma}$ on its stability, we generate a random network, shock one individual randomly, and then evaluate (according to the algorithm in Section A.1 of the Appendix) the total percentage of nodes in the network that have failed financially S—our measure of the network's instability. Each simulation is repeated 1,000 times for each set of parameter values with the share of failing nodes S averaged across iterations. Each iteration generates a unique graph $\mathcal{G}(N, G)$ with a network structure that conforms to an exogenously imposed financial wealth distribution and level of total wealth.[32] We follow the below procedure, adapted from Elliott et al. (2014a):

Step 1 Generate a static, directed random network $\mathbf{G}$ with parameter d_i represented by a truncated Pareto probability distribution. (The distribution is truncated to isolate the effect of γ for a given d. At each level of γ a maximum in-degree is set so that d remains constant.)

Step 2 Derive the cross-holdings matrix $\mathbf{C}$ from $\mathbf{G}$ using Equation (1).

Step 3 Calculate individuals' starting values $v_i \; \forall \; i \in n$, given an initial real asset price of $p_k = 1$, and determine failure threshold values $\underline{v}_i = \theta v_i$ for some $\theta \in (0, 1)$.

Step 4 Randomly choose an individual j to experience a negative income shock and decrease its real asset price to $\tilde{p}_j = \lambda p_j$.

Step 5 Assume all other real asset prices remain at 1 and calculate the number of nodes failing according to the algorithm in Section A.1 of the Appendix.

The set of all nodes Z_T who have failed financially, calculated at the algorithm's terminal step,

[32] Additional simulations (not reported) considered $n = 500$ and $n = 1,000$ and gave indistinguishable results. For computational ease, all simulation results are generated with $n = 100$.

yields the share of nodes in the network who have failed S. Results are reported with a graph of S against the wealth inequality parameter γ for varying levels of aggregate wealth d.

4.2 Calibration

We briefly summarize the choice of exogenous parameters in our simulated static random network models. (See Table 2.)

The share of an individual's net worth that can be securitized (c) characterizes the percentage of future income flows claimed by creditors in the model. An analogous, and available, macroeconomic variable measuring the burden of liabilities is the debt service ratio (DSR), the share of an individual's income repaying debt. Aggregate estimates from Drehmann & Juselius (2012) require making several assumptions concerning average credit maturity, lending rates, and total outstanding credit. Across a panel of both advanced and developing economies, the aggregate debt-service ratio for households ranges from 5.1 percent in Italy in 2010 to 20.3 percent for Denmark.[33]

Because nodes in our model represent individuals or households who also produce, make financing decisions, and determine the output of the economy, we also consider the DSR of private non-financial firms and corporations. Looking at year 2010 again, Italy has a private non-financial firm aggregate DSR of 12.9 percent and Denmark's equals 29.5 percent. For non-financial corporations the rates are even higher in 2010: 40.6 percent in Italy and 55.5 percent in Denmark.

The Federal Reserve produces two similar aggregate DSR estimates for the US: household debt service payments and household financial obligations, both as shares of personal disposable income.[34] Financial obligations include rent payments on tenant-occupied property, auto lease payments, homeowners' insurance, and property tax payments. Thus its ratio is larger, peaking at 18.1 percent in the fourth quarter of 2007 while the DSR was only 13.1 percent in the same period. The BIS data for private non-financial firms and also corporations in the US in 2010 are 15.8 percent and 39.4 percent, respectively.

[33] Data are available online at http://www.bis.org/statistics/dsr.htm

[34] Data are available from FRED online.
Household debt service payments series: https://research.stlouisfed.org/fred2/series/TDSP
Household financial obligations series: https://research.stlouisfed.org/fred2/series/FODSP

Heterogeneity of debt burdens may skew aggregate estimates, thus we examine their distributions. In 1989 and 2010 in the US, for example, top wealth holders have a greater DSR than middle portions of the wealth distribution but lower than the household average. (See Figures A.2.1 and A.2.2 in Section A.2 of the Appendix.) Generally, BIS household aggregate estimates are lower than averages calculated from household survey data for overlapping years.[35]

We consider $c \in [0.05, 0.5]$, which captures the full range of DSR estimates. Letting variable c take a value of 0.3 in our baseline scenario models an economy with reasonable household cash flow obligations. Higher c values are more akin to firms and corporations than individuals, but more congruent with the units of analysis in the network literature (Section 3).

In the event of a financial failure, such that $v_i < \underline{v}_i = \theta v_i$, an individual incurs bankruptcy costs or some increased economic burden as a consequence of their depressed net worth. We follow Elliott et al. (2014a) and let θ take on a range of values in [0.8, 0.98]. This provides a wide enough spectrum such that individuals are either very robust to valuation changes or incredibly sensitive.

Since the advent of the US Bankruptcy Act in 1978, the majority of consumer bankruptcy cases are filed under Chapter 7 protection, a form of bankruptcy in which assets (above some exemption threshold) are liquidated to pay off creditors of secure debt but the debtor's future income streams are untouched. For example, in 2014 approximately two thirds of all consumer bankruptcy petitions filed in US courts were under Chapter 7.[36] Our model assumes that, as in Chapter 7, financially failing individuals liquidate their remaining asset position to cover their failure costs. Because failure costs equal the value of the individual's wealth after failure in period t, or $\beta_i = v_{i,t}$, a failed individual's wealth drops to 0 after incurring bankruptcy costs and collateral wealth is lost.

Recall that, in our model, an income shock lowers an individual's human capital price, so that $\tilde{p}_i = \lambda p_i = \lambda$. A negative shock may decrease an individual's labor-earning capacity by varying amounts, depending on an individual's level of savings, the number of wage earners in a household, support systems of friends and family and other financial coping mechanisms. The human capital price decline could be very large if, for example, it was caused by some physical injury preventing

[35]The distribution of household DSRs is calculated using Survey of Consumer Finance (SCF) data for the US and Luxembourg Income Study (LIS) data for France and other countries (not shown).

[36]Data are available online at http://www.uscourts.gov/statistics-reports/bapcpa-report-2014.

a wage earner from earning any labor income through their human capital. In such an instance λ would be small. On the other hand, the income shock may be very small if earning capacity is not greatly inhibited, and so λ is large. The range of λ values tested is in $[0, 0.9]$. Whenever $\lambda < \theta$ a failure, and contagion, can occur.

Concerning historical US wealth inequality measurements, Wolff (1992) finds the top 1% of individuals approximately own as little as 19 percent of household wealth (excluding retirement wealth) in 1976 and as much as 38 percent in 1922. These translate to Pareto parameter values of 1.56 and 1.27, assuming top wealth shares are described by a power law.[37] In 1962, the first iteration of the Federal Reserve's household survey, the Survey of Consumer Finances (SCF)[38], found a Gini coefficient of 0.72 in wealth with a corresponding top 1% wealth share of 32 percent. In its second iteration in 1983, the SCF found a Gini coefficient for wealth of 0.74 (top wealth share of 31 percent). Using more recent SCF waves, Kennickell (2009) decomposes the wealth distribution. In 1989 the top 1% owned 28.3 percent of financial assets and in 2007 it owned 31.5 percent. Assuming a power law describes top wealth shares for the US in those years, the equivalent Pareto parameters are 1.38 in 1989 and 1.33 in 2007.

Our values for the Pareto parameter γ are in the interval [1.025, 2.375], which corresponds to a range of Gini coefficients from 0.9524 to 0.2667. The corresponding range of top 1% shares is from 89.4 percent to 6.95 percent. The parameter space is credible and within the range of empirical estimates of wealth, asset, and liability inequalities estimated in Section 3 and in the literature.[39]

Changes in γ also change the mean $d = E[d_i]$ of the in-degree distribution $f(d_i)$. Therefore, we must truncate the Pareto distribution in order to hold d constant as γ varies. In this manner we may isolate the distribution effect from the aggregate wealth effect. With $n = 100$, possible d values are restricted to the interval [1, 2]. For example, suppose $\gamma = 2.375$ (minimal inequality). The maximum possible d_i is 99 (it is not feasible to have $d_i \geqslant n$). When $\max\{d_i\} = 99$ and $\gamma = 2.375$, then $d = 2$ and represents an upper bound on expected in-degree values under our

[37]Solve for γ in $S(0.01) = 100^{\frac{1-\gamma}{\gamma}}$.

[38]The earliest Federal Reserve Board wealth survey was called the Survey of Financial Characteristics of Consumers.

[39]See Vermeulen (2014), Table 8, for Pareto parameter estimates which merge Forbes billionaire data with national surveys, such as the SCF. In his broad survey of power laws in economics, Gabaix (2009) finds 1.5 to be the median estimate found for top wealth.

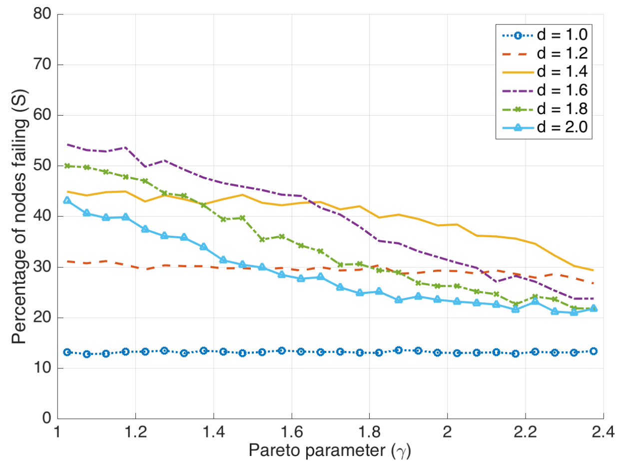


Figure 8: BASELINE MODEL
NOTES: Aggregate wealth is increasing in expected in-degree d. Calibrated with $c = 0.3$, $\theta = 0.92$, and $\lambda = 0$. As γ increases wealth inequality decreases. The domain of $\gamma = [1.025, 2.375]$ corresponds to Gini coefficients of [0.952, 0.267] and top 1% wealth shares of [0.894, 0.070]. Percentage of financial failures is average of 1,000 iterations.

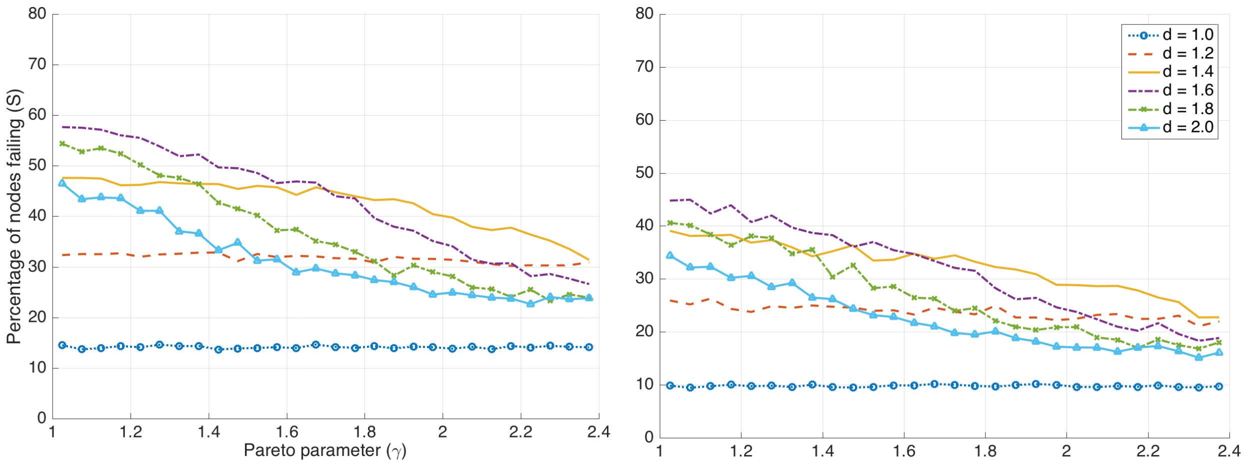
Pareto distribution. For each level of γ we adjust the maximum d_i accordingly.

Our baseline model calibration is the fullowing: $c = 0.3, \theta = 0.92, \beta_{i,t} = \underline{v}_{i,t}, \lambda = 0, \gamma = [1.025, 2.375]$ and $d = [1, 2]$. The full range of calibrations is summarized in Table 2.

4.3 Results

Results from our baseline simulation (Figure 8) illustrate that as γ decreases (inequality rises), the share S of individuals in the economy failing financially increases, but only when the network is sufficiently wealthy. Wealth inequality, in other words, is destabilizing only when the economy attains a minimum level of wealth. In our baseline model this approximately occurs when $d = 1.4$. At or above this level of financial wealth, increasing wealth inequality causes greater financial contagion and therefore a greater likelihood of financial crisis. The positive contribution of inequality on instability is most pronounced when our network's wealth has an expected in-degree of 1.6, but remains significant for higher levels of wealth as well.

Unlike wealth inequality, the effect of increasing aggregate wealth on stability is notably non-monotonic. Initial increases in aggregate wealth (from $d = 1.0$ to 1.2) increase the share of financial failures but are immune to any effects from inequality. At moderate levels of aggregate wealth ($d = 1.4$) instability is higher still, but now inequality begins to have a destabilizing impact as it



(a) Poorest node ($\min\{v_i\}$) shocked.

(b) Richest node ($\max\{v_i\}$) shocked.

Figure 9: TARGETED SHOCKS

NOTES: Aggregate wealth is increasing in expected in-degree d. Calibrated with $c = 0.3$, $\theta = 0.92$, and $\lambda = 0$. As γ increases wealth inequality decreases. The domain of $\gamma = [1.025, 2.375]$ corresponds to Gini coefficients of [0.952, 0.267] and top 1% wealth shares of [0.894, 0.070]. Percentage of financial failures is average of 1,000 simulations.

goes up (γ decreases). The strongest effect of wealth inequality occurs in a moderately wealthy network ($d = 1.6$), when moving from very low wealth inequality to very high inequality roughly doubles the size of the contagion—from around 25 to over 50 percent of the network failing. Finally, at the highest levels of aggregate wealth ($d \geqslant 1.8$), inequality remains positively and significantly related to contagion, however the level, or the share of the network failing financially, is smaller than at moderate levels of wealth—nearly 20 percentage points less at some levels of inequality.

We emphasize two results revealed in our simulations:

1. wealth inequality positively increases network instability for moderate to wealthy networks;
2. and aggregate wealth has an inverted U-shaped relationship with instability—initially increasing, but then decreasing.

The network economy is therefore most unstable, or vulnerable to negative shocks, when it is both wealthier (higher d) and unequal (low γ). The model also reveals an important interaction between an economy's level of wealth inequality and total aggregate wealth, reflecting the "robust-yet-fragile" nonmonotonicity found in other network models.[40]

Financial contagion occurs independent of the node subjected to the random income shock.

[40] Gai & Kapadia (2010), Nier et al. (2007), and Elliott et al. (2014a).

Figure 9 depicts two scenarios of identically calibrated networks. In the left panel, the poorest node in the network receives the negative income shock and in the right the richest node is shocked. The level of contagion, while significant and nearly identical to our baseline model in both, is different as is the likelihood of financial crisis. When the poorest node ($\min\{v_i\}$) receives the income shock, a greater share of the network fails for both a given level of inequality and aggregate wealth than when the richest node ($\max\{v_i\}$) is shocked. This makes sense because poorer nodes have more liabilities, and thus their failure spreads to a greater number of nodes than when the richest node is shocked. The stronger effect on instability of shocking the poorest node is more muted at lower aggregate wealth levels. When the richest node is shocked, networks are more robust by over ten percentage points for the wealthiest networks ($d \geqslant 1.6$) and approximately five percentage points for the least wealthy networks ($d = 1$).

The overall pattern of our baseline model, observed when a random node is shocked, however, persists: increasing wealth inequality (decreasing γ) causes a greater share of individuals to fail in networks of at least moderate wealth while increasing the aggregate wealth (increasing d) of the network is initially destabilizing but then stabilizing.

4.3.1 Regular Graphs

To emphasize the importance of both aggregate wealth and the financial wealth distribution on network stability, we study random regular graph simulations. Regular graphs feature equal in-degrees and thus represent perfect financial asset equality in our model. The only parameters changing are c, the percentage of future cash flows owed by an individual to other claimants, and d, the in-degree of all individuals. No longer restricted by the degree distribution parameter γ, d can take on a broader set of values. Results are presented in Figure 10.

As d increases the aggregate wealth of the network increases. When $c > 0.15$, there exists a stark pattern: the share of nodes failing increases sharply when aggregate wealth is low and increasing, but quickly drops again as aggregate wealth increases beyond some level. (The particular level depends on c.) Increasing c extends the in-degree values for which instability is high, before dropping to zero in even wealthier networks. Like our models in Figures 8 and 9, the equal network displays

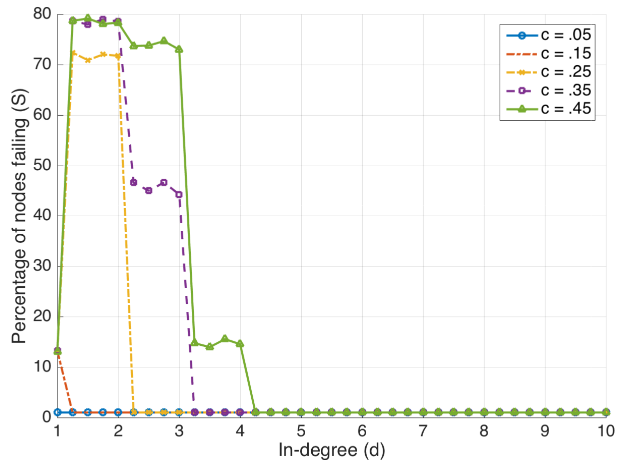


Figure 10: REGULAR (EQUAL) NETWORK
NOTES: Regular network contains fixed in-degree d_i for each node, hence there exists perfect wealth equality. Aggregate wealth is increasing in expected in-degree d. Calibrated with $\theta = 0.92$, and $\lambda = 0$. Percentage of financial failures is average of 1,000 iterations.

increasing instability as aggregate wealth increases from low to moderate levels, but decreasing instability as wealth increases further. Decreasing c or financialization at the intensive margin, however, also significantly lowers instability.[41]

Simulation results for the full range of calibrated parameter values described in Table 2 are presented in the Appendix, Section A.3. The model is particularly sensitive to the c parameter—as evidenced by the regular network simulations in Figure 10—as well as the θ parameter, , the measure of an individual's personal robustness under financial stress, or the economy's ability to absorb depleted cash flows on asset claims. The parameter λ, inversely proportional to the size of the income shock $\tilde{p}_i = \lambda p_i$, is nearly indiscriminate in its effect on contagion (see Figure A.3.3). So long as the condition $\lambda < \theta$ holds, an initial negative income shock will always cause at least one financial failure which will catalyze contagion within the network.

5 Reduced Form Empirical Model

Simulation results exhibit the following consistent relationships in our network model:

1. In sufficiently wealthy networks, decreasing the Pareto shape parameter γ increases wealth

[41]The step-function-like behavior of the regular network results are due to the fact that individuals must have integer values of $d_i = d$. A rounding function in the program simply rounds up to the next integer.

inequality and increases the share of nodes failing S, and

2. increasing the expected in-degree d of the network's nodes increases aggregate wealth and first increases, then decreases, the share of nodes failing S. (See Figures 9a–9b.)

The effects are summarized more succinctly by the partial differentials: $\frac{\partial S}{\partial \gamma} < 0$, but only above a certain level of d, and $\frac{\partial S}{\partial d} > 0$ and $\frac{\partial^2 S}{\partial d^2} < 0$, where $S = S(\gamma, d, c, \theta, \lambda)$. This yields the following two hypotheses to test empirically.

$\mathcal{H}_1$ Wealth inequality increases the probability of financial crisis in wealthy economies.

$\mathcal{H}_2$ Aggregate wealth has an inverted U-shaped relationship with financial instability.

To derive our reduced form model, we first redefine each effect in isolation before defining their interaction as linearly related to the percentage of failures in the network. While the Pareto shape parameter γ describes the skewness of the in-degree distribution across the entire network, its inverse γ^{-1} is a direct measure of network inequality. The top 1%'s share of financial wealth, derived from the Pareto shape parameter on the left-hand side, below, gives us

$$100^{\frac{1-\gamma}{\gamma}} \equiv \frac{d_1}{\sum d_i} \tag{8}$$

where $d_1 = \max\{d_i\}$ from our 100 node network and $\sum d_i$ is aggregate wealth.

Next, we redefine our aggregate financial wealth measure d. It is possible to sum the number of financial assets each individual owns as in Equation (8). Dividing it by total network income, which we defined as $\text{Tr}(\mathbf{D})$ (where Tr is the trace of a matrix), yields an aggregate wealth-income ratio:[42]

$$d = E[d_i] \equiv \frac{\sum d_i}{\text{Tr}(\mathbf{D})} = \frac{W}{Y}. \tag{9}$$

If, as we argue, the percentage of individuals failing in a financial network S is a latent variable representing instability, or the likelihood of a financial crisis, a dependent variable *crisis* is the corresponding observed binary indicator. For example, suppose whenever S is above 70 percent *crisis* takes a value of 1 and 0 otherwise, then $crisis = I_{S>0.7}$. We remain agnostic, however, as to

[42] Recall that the real asset claims matrix $\mathbf{D}$ is equal to $\mathbf{I}$.

the precise threshold.

Wealth inequality is empirically measured as the top 1%'s share of aggregate net worth $top1nw$ and aggregate wealth is measured relative to national income $\frac{W}{Y}$. After substituting these empirical measures for the theoretical ones implied by our model in Equations (8) and (9), interacting them to capture their jointly deterministic role in network instability, arranging in a linear probability model with a crisis indicator as the dependent variable, lagging, and adding country and year fixed effects we arrive at the linear model below.

$$crisis_{it}^{k} = \delta_i + \delta_t + \beta_1 top1nw_{it-2} + \beta_2 \left(\frac{W}{Y}\right)_{it-2} + \beta_3 top1nw \times \left(\frac{W}{Y}\right)_{it-2} + \gamma' \mathbf{X}_{it-2} + \varepsilon_{it} \tag{10}$$

Dependent variable $crisis_{it}^{k}$ is a binary indicator of a financial crisis of type k for a given country i and year t, $top1nw$ represents the net worth held by the top 1% of households, and $\frac{W}{Y}$ is the aggregate wealth-income ratio for a given country. The matrix $\mathbf{X}$ contains a set of control variables specified in the next section. [43] Lag-length was determined by information criteria.

Testing our second hypothesis requires adding a quadratic specification for aggregate wealth:

$$crisis_{it}^{k} = \delta_i + \delta_t + \beta_1 top1nw_{it-2} + \beta_2 \left(\frac{W}{Y}\right)_{it-2} + \beta_4 \left(\frac{W}{Y}\right)^2_{it-2} + \beta_3 top1nw \times \left(\frac{W}{Y}\right)_{it-2} + \gamma' \mathbf{X}_{it-2} + \varepsilon_{it}. \tag{11}$$

The linear probability model (LPM) is chosen because our emphasis is on the positive or negative marginal effects of wealth inequality and aggregate wealth, which, based on our simulation results, can interact nonlinearly. Teasing out the marginal effects in a fixed effects logit model would be more difficult to interpret. Second, we use this specification because our model is not primarily intended as a predictive tool but rather as an analytical measure of historical significance. Country and year fixed effects are employed to account for the endogeneity any macroeconomic system entails, the between-country correlation of crises—an imperfect remedy—, and the overall irregular spacing of our sample observations.[44] Significant results merely support the financial network framework for thinking about macroeconomic effects from wealth distributions.

[43] Unfortunately, time-series data of sufficient span are unavailable for other key parameters like c and θ.

[44] A two-way fixed effects logit estimator, as elegantly laid out by Charbonneau (2014), is not programmed and is thus far unobtainable.

5.1 Marginal Effects

The marginal effects of wealth inequality $top1nw$ and aggregate wealth $\frac{W}{Y}$ on the likelihood of a financial crisis imply, from Equation (10), that

$$\frac{\partial crisis_{it}^{k}}{\partial top1nw_{it-2}} = \beta_1 + \beta_3 \left(\frac{W}{Y}\right)_{it-2} \lesseqqgtr 0 \tag{12}$$

and

$$\frac{\partial crisis_{it}^{k}}{\partial (\frac{W}{Y})_{it-2}} = \beta_2 + \beta_3 top1nw_{it-2} \lesseqqgtr 0. \tag{13}$$

Coefficients β_1 and β_2 are now difficult to interpret. For example, if β_1 is to be economically significant then $\frac{W}{Y}$ must equal zero, an impossible outcome. An analogous scenario afflicts β_2. Instead we focus on the sign and significance of the overall marginal effects, and the proportion of sample observations under which they are positive or negative.

If we reject the first null hypothesis ($\mathcal{H}_1 : \beta_3 = 0$), in favor of a positive alternative where $\beta_3 > 0$, our wealth inequality network mechanism may be one plausible interpretation of the relationship between wealth inequality and financial instability. Figure 8 summarizes these effects: Increasing wealth inequality (lower γ), given a sufficient level of wealth, increases instability.

From Equation (11) we may directly consider the nonmonotonic effects of aggregate wealth on instability. The marginal effect becomes

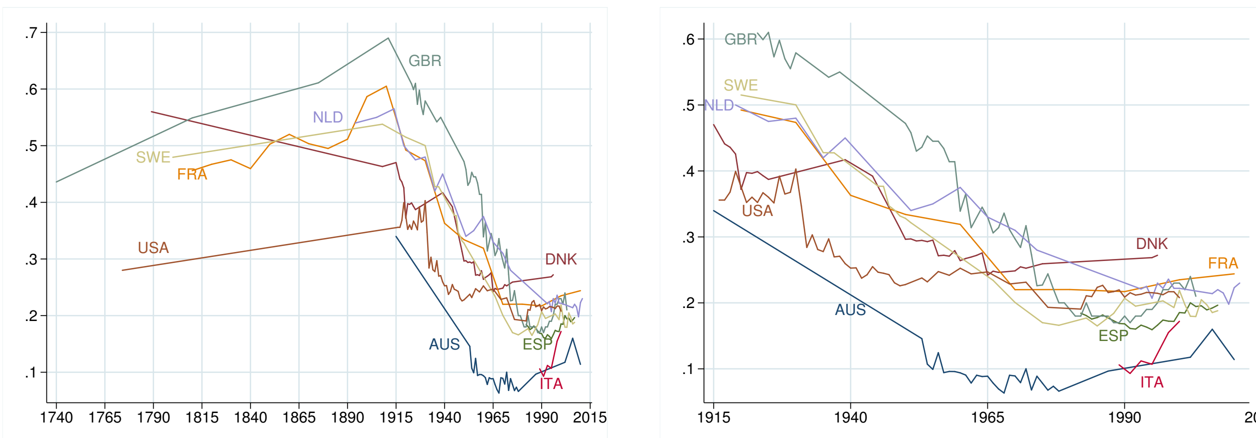
$$\frac{\partial crisis_{it}^{k}}{\partial (\frac{W}{Y})_{it-2}} = \beta_2 + 2\beta_4 \left(\frac{W}{Y}\right)_{it-2} + \beta_3 top1nw_{it-2} \lesseqqgtr 0. \tag{14}$$

Rejecting the second null hypothesis ($\mathcal{H}_2 : \beta_2 = 0 = \beta_4$) in favor of an alternative, where $\beta_2 > 0$ and $\beta_4 < 0$, would suggest aggregate wealth displays an inverted U-shape relationship with instability, first increasing but then decreasing.

6 Data

Wealth Inequality

The net worth held by the top 1% of households is our measure of wealth inequality.[45] This is intuitive since our theoretical network's wealth distribution was Pareto, and estimated the distribution of top financial assets. A survey by Roine & Waldenström (2015) collects ten national time series of wealth concentration.[46] Data begin with a single observation in 1740 for the UK and continue through 2012. Many series are sporadic with large gaps between observations (see Figure 11 below). However, there is a distinct overall trend. Each country's top wealth shares peak near the turn of the twentieth century, decline, and then begin increasing at various points between the 1950s and 1960s. (See Figure 11b.) Australia, Sweden, and the UK show strong increases over the last 40 years, while others are more mild, such as France, the Netherlands, and the US.



(a) 1740–2012 **(b)** 1915–2012

Figure 11: Top 1% Share of Net Worth
Sources: Roine & Waldenström (2015), Brandolini et al. (2006), and Alvaredo & Saez (2009).

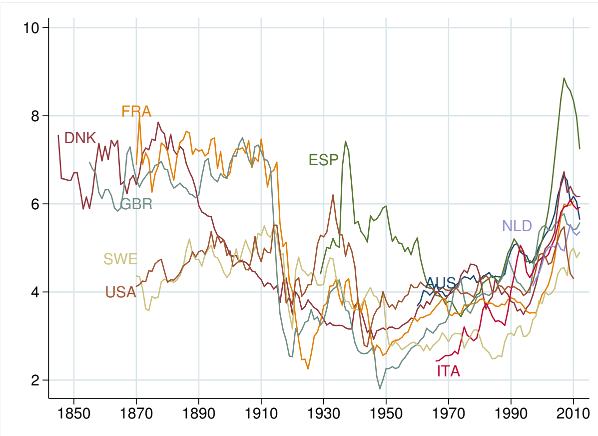
Aggregate Wealth

Piketty & Zucman (2014) estimate a country's national wealth, while calling it the capital-income ratio, by summing all marketable capital assets at their current price levels.[47] Their capital-income ratio includes productive capital such as land and factories, financial capital like pensions and life

[45] Surveys from France, the UK, and US are based on individual data.

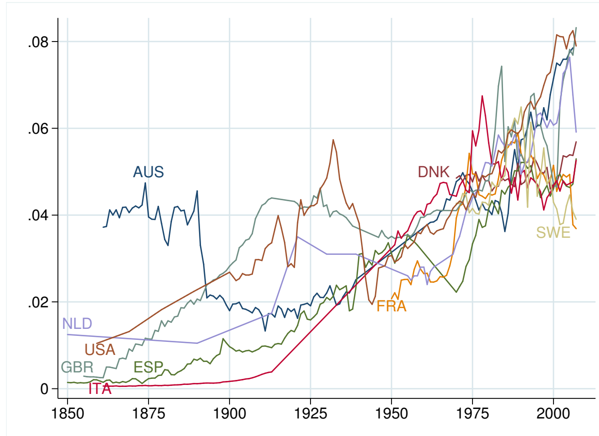
[46] Available online at http://www.uueconomics.se/danielw/Handbook.htm. A complete list of their data sources for historical wealth inequality can be found in table A1 of Roine & Waldenström (2015). Data for Italy (Brandolini et al. (2006)) and Spain (Alvaredo & Saez (2009)) supplement the Roine & Waldenström (2015) data. Each country's time series is dependent on sampling methods and weighting, tax evasion, mortality rate calculations, and the basic unit of measurement. Despite such heterogeneous methodology, but also given the lack of a consistent historical survey across countries, we employ the data aware of these shortcomings. Roine & Waldenström (2015) also cite comparison studies of household versus individual surveys which find "no important differences."

[47] Reviewers of *Capital in the Twenty-first Century* such as Varoufakis (2014) and Blume & Durlauf (2015) have faulted Piketty for conflating wealth with capital.



Sources: Alvaredo et al. (2015), Waldenström (2015), and Abildgren (2015)

Figure 12: Aggregate Wealth-Income Ratios



Source: Philippon & Reshef (2013)

Figure 13: Finance Value Added Share of Income

insurance, and also capital assets like art, but excludes durable goods, an important source of wealth and collateral for low-income households, claims on future government spending and transfers, and human capital—an important determinant of contemporary incomes. We call this the aggregate wealth-income ratio.

Aggregate wealth-income ratio data from Piketty & Zucman (2014) cover a panel of seven countries from 1845 through 2012.[48] It is supplemented with national wealth data estimates for Sweden (from Waldenström (2015)) and Denmark (from Abildgren (2015))[49] and both adhere to the methodological approach of Piketty & Zucman (2014). Some general trends emerge (see Figure 12): all countries having an increase in aggregate wealth over the last 40 years, with some beginning around 60 years ago; all countries except Sweden and the US had high aggregate wealth in the nineteenth century and the UK and France have notably returned to those levels—the contention of Piketty & Zucman (2014).

Our two central explanatory variables (wealth inequality and aggregate wealth) are available for nine countries: Australia, Denmark, France, Italy, the Netherlands, Spain, Sweden, the UK, and the US. Depending on model specification and estimation method, our panel contains up to 273

[48]The *World Wealth and Income Database* (WWID), formerly known as the *World Top Incomes Database* (WTID), is partially derived from contributions like Piketty & Zucman (2014). Data are available online at http://topincomes.g-mond.parisschoolofeconomics.eu/. The WWID plans to eventually include wealth concentration data to complement its existing top income share data.

[49]See Waldenström (2014) for the creation of the Swedish National Wealth Database (SNWD).

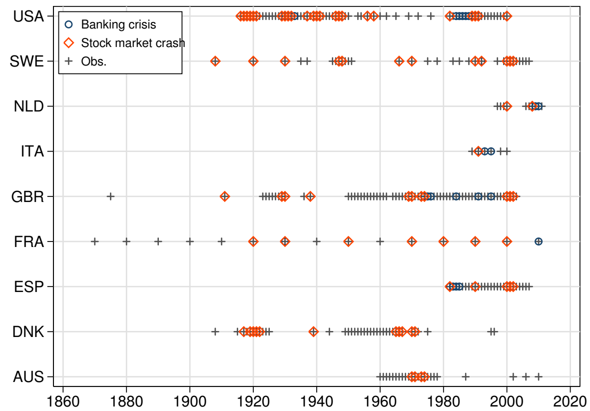


Figure 14: CRISES TIMELINE

observations. However, it is unbalanced. There exist 105 unique years and one fifth contain only a single country.

Financial Crises

Binary crisis indicators invite scrutiny since they are largely determined through professional consensus that is established by precedent and acceptance in the relevant literature. Our data come from Reinhart & Rogoff (2010), one such accepted source, and specify a given country, year and crisis type. The authors define financial crises granularly, distinguishing between six crisis types.[50] We focus on two: banking crises and stock market crashes. (The others, we argue, are more politically than economically determined.) A banking crisis is defined as either a series of bank runs that culminate in the public takeover of at least one institution, or the closure, merging, takeover, or government assistance of one important institution. A stock market crash is defined more objectively. When multi-year real returns are at least -25 percent, a crash is deemed to have occurred. Crisis episodes, in our nine country panel, are summarized in a timeline in Figure 14. We do not consider existing continuous measures of financial stress because they only begin in the 1990s.[51] Tables 3–4 summarize the number of crisis episodes per country.

[50] Currency crises, inflation crises, stock market crashes, domestic and external sovereign debt crises, and banking crises.

[51] Hakkio & Keeton (2009), for example, describe an index constructed and distributed by the Federal Reserve Bank of Kansas City. It is composed of 11 variables measuring different rate spread and volatility indices. Minsky (1993) suggests a meaningful financial instability index must incorporate 1) the relative weight of three types of finance units in the economy (i.e. hedge, speculative, and Ponzi financing), grouped by their outstanding liabilities and ability to finance them from current and future cash flows; 2) the willingness of the central bank to act as lender of last resort in a downturn; and 3) the willingness of the government to increase deficit spending to sustain income and employment during a downturn.

Controls

To account for a country's level of financial market development, such that increases in wealth-income ratios or top wealth shares are not simply reflecting the size of a country's financial markets, we include data on the overall share of value added to GDP by the financial sector over time. Data, from Philippon & Reshef (2013), begin as early as 1850 for some countries and continue through 2007 (see Figure 13).

Additional controls, from Roine et al. (2009), include a measure of financial development (the sum of bank deposits and stock market capitalization) used to estimate a proxy for the rate of return on capital, and private sector credit—both as a share of GDP.[52] Data begin in 1900 and continue through 2006. (See Figures A.4.1 – A.4.2 in the Appendix.) Including total private credit accounts for the most cited determinant of financial crises in the literature.[53] Top marginal tax rates (Figure A.4.3) are included since they directly determine savings, which accumulate into wealth, and can represent a form of redistribution—cited as a destabilizing cause of the US subprime mortgage crisis.[54] With the full set of control variables our panel data set is just 134 observations for 6 countries (Australia, Spain, France, Sweden, the UK, and US).

Asset price bubbles, and the business cycles which generate them, are the dominant economic theory for financial crises. To support our argument that the distribution of assets is contributing to financial instability, we attempt to control for these factors by including proxies for the rate of return on capital as well as overall growth. Piketty (2014) presents a theoretical relation between increasing wealth inequality and a positive $r - g$ and Fuest et al. (2015) corroborate its empirical validity. Controlling for both ensures that any apparent effect of wealth inequality on instability is not actually being driven by cyclical determinants of wealth inequality or asset price bubbles. We proxy for r by differencing over changes in financial development and for g with the percent change in income per capita. (See Table 5 for summary statistics across variables.)

[52] See Table 1 in Roine et al. (2009) for detailed documentation of the original papers and sources of each series.
[53] For example, see Bordo & Meissner (2012) or Schularick & Taylor (2012).
[54] Bordo & Meissner (2012) and Rajan (2011)

7 Empirical Results

We first present OLS results for various specifications of the reduced form linear probability model in equation (10). Of primary concern are the marginal effects of wealth inequality and aggregate wealth on crises (Equations (12)–(13)). Inferring fitted probabilities is not practicable since in many instances values may be negative—and technically uninterpretable.

Results estimating the likelihood of banking crises are presented in Table 10 and the likelihood of stock market crashes in Table 11. In both types of crises we find statistically significant results on the term interacting wealth inequality with aggregate wealth-income ratios for the model specification including financial sector size (Column 2), our preferred specification when considering both parsimony and sample size. This model explains over 57 percent of the variation in banking crises and 82 percent of the variation in stock market crashes in our larger panel of nine countries.

The interacted term of inequality and wealth is significant (at 5%) in our preferred banking crisis model (Table 10, Column 2), but insignificant in all other specifications. In contrast, the interaction in our stock market crash model (Table 11) is significant across specifications, and very significant (1%) in our preferred model (Column 2). One reason may be that the occurrence of a banking crisis is defined by government intervention, an inherently political and discretionary decision. A second is that researchers may have varying definitions of a systemically important institution (which requires the federal aid). Given these imprecise definitions, observations with positive banking crises may lack enough within-group variation to demonstrate any consistent relationship. Financial contagion that prompts government intervention and bailouts in one circumstance may not seem sufficiently dire to officials in an alternate scenario and thus similar circumstances may have opposing outcomes. In contrast, stock market crashes are defined by predetermined empirical changes in stock market indices and not ad hoc political interventions, one reason that parameter constancy and significance exist in those models. The simplest explanation may be the higher frequency of stock market crashes in our data (Table 4).

7.1 Marginal Effects

Wealth inequality and aggregate wealth alone have negative but insignificant effects on banking crises (Table 10, Column 2). The marginal effect of aggregate wealth on banking crises is

$$\frac{\partial crisis^b_{it}}{\partial(\frac{W}{Y})_{it-2}} = -0.187 + 1.845 top1nw_{it-2}, \tag{15}$$

and remains positive whenever top wealth shares are greater than 0.1014—or above the 10th percentile in subsample 2. The various levels of wealth inequality that satisfy a positive marginal effect of aggregate wealth on banking crises are summarized in Figure 15a, plotting the magnitude of the marginal effect against wealth inequality levels. It compares observations across the entire sample of data with the specific subsample the model was estimated on. The distribution of observations for the horizontal axis variable (wealth inequality in Figure 15) is shown by the kernel density plot, where dashed vertical lines indicate the median.

The positive marginal effect of aggregate wealth on stock market crashes, derived below, is less overwhelmingly positive.

$$\frac{\partial crisis^s_{it}}{\partial(\frac{W}{Y})_{it-2}} = -0.570 + 2.306 top1nw_{it-2}. \tag{16}$$

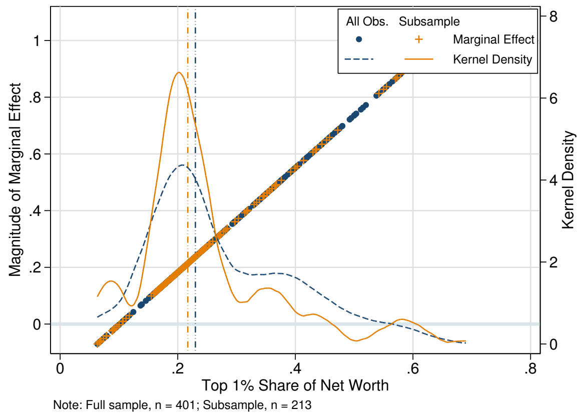
Now, in order for the marginal effect to be positive, top wealth shares must be greater than 0.247 according to the model specification above—past the median values of either sample (see Figure 15b).

Next, we consider the marginal effects of wealth inequality. Concerning banking crises (Table 10, Column 2) we find the following:

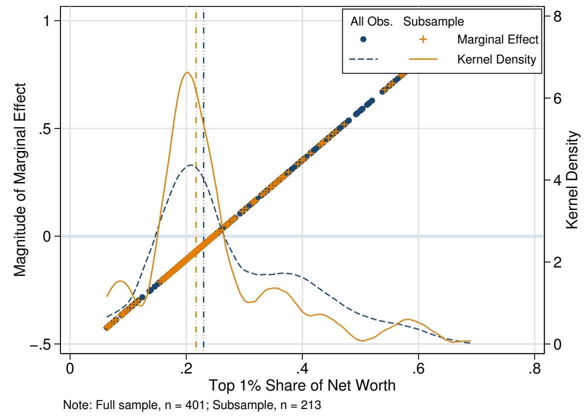
$$\frac{\partial crisis^b_{it}}{\partial top1nw_{it-2}} = -2.615 + 1.845 \left(\frac{W}{Y}\right)_{it-2} - 28.309 finsh_{it-2}. \tag{17}$$

It remains positive for all levels of the aggregate wealth-income ratio (and their corresponding financial sector shares) except for a single observation out of 1,174. (See Figure 16a.)

The marginal effect of wealth inequality on stock market crashes, from Table 11, Column 2, is

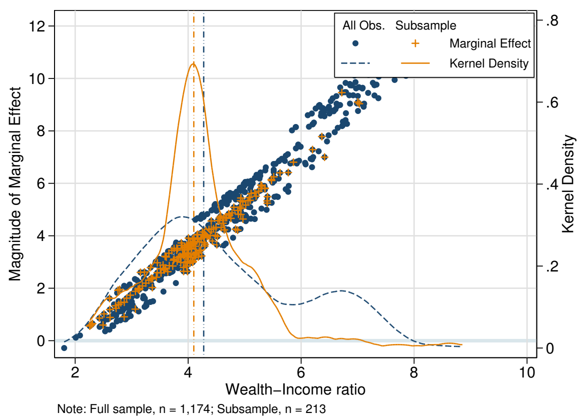


(a) Banking Crises

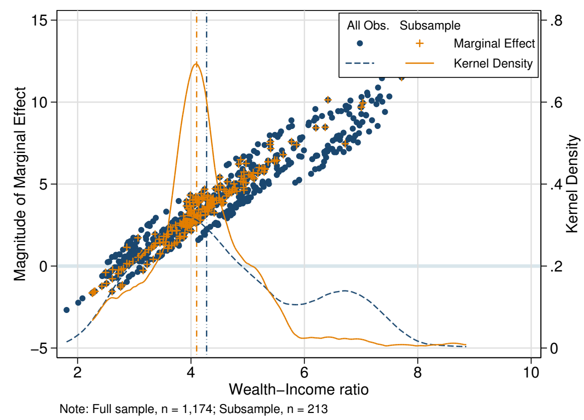


(b) Stock Market Crashes

Figure 15: Marginal Effect of Aggregate Wealth on Likelihood of Crisis: LPM



(a) Banking Crises



(b) Stock Market Crashes

Figure 16: Marginal Effect of Wealth Inequality on Likelihood of Crisis: LPM

similarly positive and increasing.

$$\frac{\partial crisis^s_{it}}{\partial top1nw_{it-2}} = -8.616 + 2.306\left(\frac{W}{Y}\right)_{it-2} + 50.426 finsh_{it-2}. \tag{18}$$

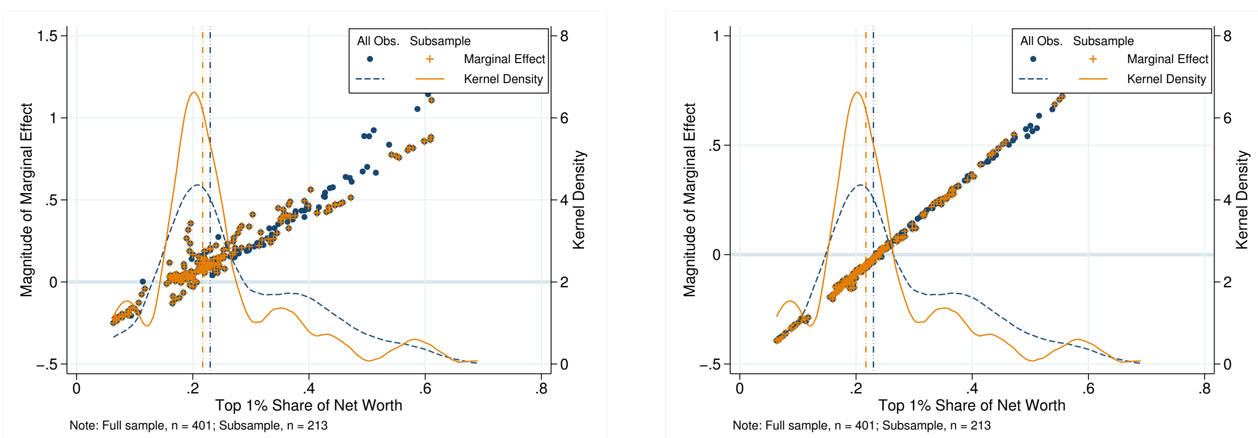
It remains positive when wealth-income ratios are above the 2^{nd} percentile of ratios among the model's subsample observations and the 10^{th} percentile for the full data series (Figure 16b.)

Overall we reject our first null hypothesis ($\mathcal{H}_1 : \beta_3 = 0$), favoring the positive wealth inequality-instability network interpretation. Our results indicate that wealth inequality has a positive and significant marginal effect on the likelihood of both of our financial crisis measurements. The positive slopes observed in Figure 16 supports our model's contention that the effect of wealth inequality on instability is increasing in aggregate wealth. While inequality's marginal effects are positive on both crises, it is unsurprising that the stock market crash model's estimates are more significant and consistent given their apolitical, objective definition and greater prevalence.

These results support our contention that the distribution of wealth is an important component in determining the likelihood of some future financial crisis in a wealthy economy. A rising maldistribution of wealth implies any negative income shock has the potential to hurt the finances of a larger fraction of the economy wherein each individual will be less resilient to depressed cash flows because of the interdependency on other individual cash flows.

7.2 Aggregate Wealth and Instability

Our theoretical model predicted an inverted-U relationship between rising aggregate wealth and instability. That is, as the network became wealthier instability increased but eventually began to decrease as aggregate wealth continued to grow. Least squares estimates of Equation (11) are presented in Table 12, all based on the second specification from Tables 10 and 11.



(a) Aggregate Wealth

(b) Wealth Inequality

Figure 17: Marginal Effects of Nonlinear Aggregate Wealth on Likelihood of Crisis

Though explaining between 50 and 80 percent of the variation, and again showing very significant results for the interacted term between wealth inequality and aggregate wealth, no coefficients of wealth-income ratio terms suggest a plausible inverted-U relationship. The only coefficients that actually lead to an inverted-U graph are from the stock market crash model, but it is increasing for extremely negative values of wealth—an impossible situation—and decreasing for all nonnegative values. Also, the marginal effects of aggregate wealth on crises (Equation (14) and Figure 17) are positive and increasing—exactly the opposite of the anticipated outcome.

While we still reject our second hypothesis ($\mathcal{H}_2 : \beta_2 = 0 = \beta_4$), we cannot reject it an favor of an alternative that indicates a negative quadratic relationship between network wealth and instability as suggested by our model. One possibility is that the economies in our sample have all attained sufficiently high levels of aggregate wealth by the 20^{th} century that they are all on the downward sloping portion of the inverted-U curve. However, the large percentage of observations that show a significantly negative marginal effect of aggregate wealth on stock market crashes (Figure 15) leave the question unsettled.

7.3 Additional Crisis Regressors

One concern is that the above results may be influenced by the seemingly random availability of historic wealth inequality observations in our unbalanced panel data.[55] (See the timeline in Figure 14 indicating crisis episodes and data observations in our largest subsample.)

Considering this possibility, we examine long-run relationships by averaging all the variables (both independent and dependent) across five-year horizons. The dependent variable becomes continuous within the unit interval, thus capturing the relative intensity of crises over half-decade intervals. Results from estimating the reduced form two-way fixed effects model, without lags, averaged across five-year intervals show consistently positive estimates for our interaction parameter. (See Tables A.5.1–A.5.2 in Section A.5 of the Appendix.) A fully specified model is most significant when describing the relationship with banking crises, while more parsimonious models are most significant when describing the relationship with stock market crashes.

For consistent comparisons to previous estimates we focus on the second model specification (Columns 2) when examining marginal effects (Figure A.5.1). Wealth inequality demonstrates a strongly positive and increasing marginal effect on stock market crashes over five-year periods—

[55] French wealth inequality data, for example, are available only every 10 years beginning in 1870.

and remains so for 98 percent of wealth-income ratios observations. (The marginal effect of wealth inequality is also strongly positive on banking crises, though the model is insignificant. The marginal effect of wealth, not shown, is generally positive for both crisis types, but only for higher percentiles of wealth-inequality.)

To further test the constancy of the wealth inequality-financial crisis relationship, we introduce a new crisis indicator. We define a *large crisis* to be when both types occur within the same year (i.e. the intersection of financial crises). Regression results (presented in Table A.5.3 in Section A.5 of the Appendix) indicate wealth inequality interacted with national wealth is significantly and positively related to large crises in our preferred specification (Column 2). Significance goes away as controls are added and observations decline. The marginal effect of aggregate wealth on instability is positive, but only for wealth inequality levels above the median. Inequality has a positive and increasing marginal effect on the likelihood of large crises when aggregate wealth is above the 10^{th} percentile of the distribution.

Overall, the marginal effect of wealth inequality on financial instability, in the specification controlling for financial sector size, is positive and increasing. It remains so except when wealth-income ratios are in the bottom 5^{th} or 10^{th} percentiles—depending on the relative financial sector size. These results support a strong positive relationship between rising wealth inequality and financial instability, conditional on the aggregate wealth of the economy in question. Moreover, they bolster the contention of our theoretical interpersonal financial network model that the arrangement of financial links matters for future financial stability.

8 Robustness Checks

In this section we present findings on and discuss two robustness checks of our empirical results: First, the empirical relationship in Equation (10) is estimated as a fixed effects logit model; second, we substitute income for wealth as our inequality measure.

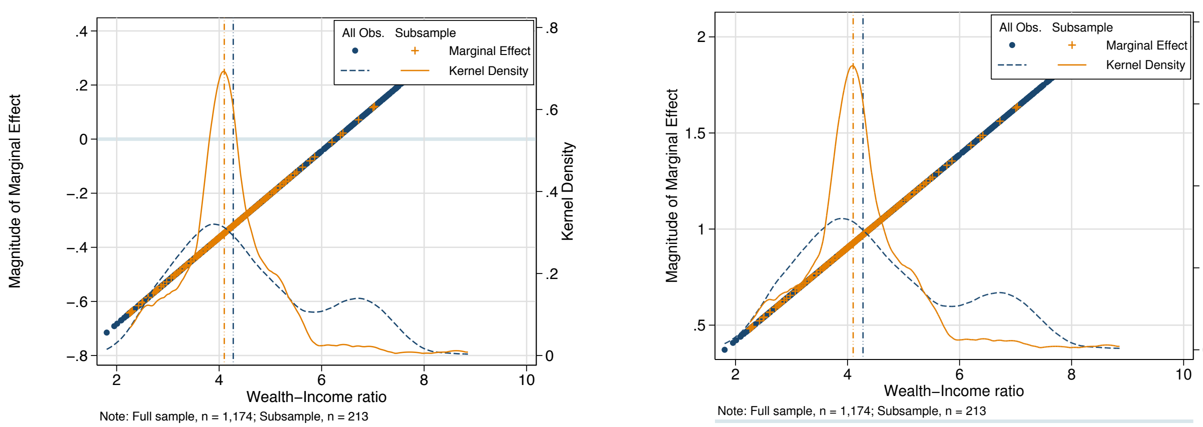
8.1 Fixed Effect Logit

The fixed effect logit model is estimated to confirm our findings from the linear probability model with two-way fixed effects. We estimate the following equation with country-level fixed effects using maximum likelihood:

$$\Pr(crisis_{it}^{k}=1)=\Lambda\left[\delta_i+\beta_1 top1nw_{it-2}+\beta_2\left(\frac{W}{Y}\right)_{it-2}+\beta_3 top1nw\times\left(\frac{W}{Y}\right)_{it-2}+\gamma'\mathbf{X}_{it-3}\right] \quad (19)$$

where $\Lambda(\cdot)$ represents the cdf for the logistic distribution.

Results estimating the likelihood of banking crises and stock market crashes are shown in Tables A.6.1–A.6.2 of the Appendix. In both of the our preferred models (Column 2), estimates are not significant—though the interacted term between inequality and wealth remains positive. The fully specified models are significant and positive in the interacted term, however a finite sample and very large coefficients suggest the specification is overdetermined. Estimating the marginal effects of wealth inequality on both crisis types yields the plots in Figure 18.



(a) Banking Crises **(b)** Stock Market Crashes

Figure 18: Marginal Effect of Wealth Inequality on Likelihood of Crisis: Logit Model

We find negative but increasing results concerning banking crises, the discretionarily coded crisis outcome, but consistently positive, and increasing, marginal effects on the likelihood of stock market crashes. While our preferred parsimonious logit model is insignificant, the logit results alone are insufficient to falsify the existence of a positive relationship between wealth inequality and financial instability, conditional on high aggregate wealth. Additional fixed effect logit results (not shown) on *large* crises, do find positive estimates of the interacted term and yield only positive marginal effects for wealth inequality.

8.2 Income Inequality

Is our emphasis on wealth inequality rather than income inequality warranted? Or, does income inequality also predict skewed cashflow network structures that are unstable? We estimate the same reduced form linear probability model with two-way fixed effects in Equation (10) and simply substitute top income shares data for top wealth shares data. Income inequality data are more common, so our panel grows to 10 countries with a maximum of 538 observations.

Estimation results are presented in Tables A.6.3 and A.6.4 in the Appendix. The impact of income inequality on financial instability is ambiguous and insignificant. Parameter estimates on income inequality and income inequality interacted with the aggregate wealth-income ratio demonstrate a large variance in both sign and magnitude when predicting both crisis types.[56]

Though insignificant, we still analyze the marginal effect of income inequality as a comparison to Figures 15 and 16 above. (See Figure A.6.1 in the Appendix.) The effect (based on specifcation 2, to mirror the wealth models) is starkly negative and decreasing for banking crises, across all wealth-income ratios. This would suggest a decreasing effect of inequality on banking crises, the opposite of our model's predictions and empirical findings for wealth inequality. The marginal effect of inequality on stock market crashes is mixed, but more positive and increasing, both in our full sample of wealth-income ratios and the specification subsample.

A Davidson & MacKinnon (1981) J-test of model specification confirms the lack of explanatory power for income inequality in our model.[57] These results do nothing to detract from our claim, and statistical evidence, that the distribution of financial assets (a stock) rather than incomes (a flow) positively influences a wealthy economy's instability.

[56] In two instances the R-squared actually decreases when appearing to add covariates between specifications because enough year dummies shave been omitted due to collinearity and thus the total number of regressors decreases.

[57] Though several problems exist in our estimation which increase the likelihood of overrejection (i.e. a finite sample and a model under test that doesn't fit well), we still fail to reject that the predicted income inequality model regressor is statistically different from zero.

9 Conclusion

Keynes once described the relationship between debtors and creditors as forming "the ultimate foundation of capitalism." In a financial capitalist economy, the debt of households and firms is typically held by financial intermediaries, and capital asset owners hold shares in intermediaries equalling those debts. The economy's balance sheet must balance, as the saying goes. Studying the asset side's distribution, we believe, helps illuminate the relationship between inequality and crisis. Jayadev (2013) concludes in his summary of the inequality-crisis literature, "wealth/net worth may be the more critical variable, especially when financial crises are driven by asset bubbles."

Our financial network model of wealth inequality and financial instability, based on the holistic approach of Elliott et al. (2014a), establishes with simulations that changes to the network topology capture two effects: First, increasing top wealth inequality, conditional on a network's overall wealth, increases instability. Second, aggregate network wealth should have an increasing and then decreasing effect on instability.

The model is a radically simplified interpretation of a financial economy, one that eliminates intermediaries and instead relies on the latent financial pathways that link individual asset and liability holders. Implicit financial links between individuals are made explicit in a directed network graph. Increasing the aggregate wealth of the network increases the overall number of links. If these explicit links are spread evenly our network model displays relative wealth equality and, consequently, is more stable in the event of a random individual's exogenous income shock. Increasing the level of wealth inequality by skewing the distribution of links between individuals (via the network's degree distribution) and also increasing the total number of financial links increases instability (measured by the share of financially failing nodes) in the event of a shock. We interpret this increase in individual financial failures, or instability, as an increase in the likelihood of a financial crisis more broadly.

To test the empirical validity of our theoretical model, a reduced-form linear probability model with two-way fixed effects was estimated using a panel of nine countries (Australia, Denmark, France, Italy, the Netherlands, Spain, Sweden, the UK, and the US) with historic data beginning in 1870. The marginal effect of wealth inequality on the likelihood of financial crises, particularly stock market crashes or both banking crises and stock market crashes, is statistically significant, positive, and increasing. The finding is robust to the frequency of observations and estimation methods. While motivated by the US case over last forty years, the positive marginal effect of wealth inequality on instability appears not only across time in the US but also across other financially advanced and wealthy economies (i.e. Australia, France, and the UK). We do not find support, however, for our model's prediction of an inverted U-shaped relationship between aggregate wealth and financial stability.

Our results strongly suggest that the two parameters, wealth inequality and aggregate wealth, are mutually important in determining economic stability. One implication is that future increases in wealth inequality (as predicted by Piketty) in the US and other financially advanced economies would increase macroeconomic instability, meaning a greater likelihood of financial crisis in the event of some negative income shock. The consequences for moral hazard, systemic risk, and too-big-to-fail among other regulatory concerns could be great. Another broader implication is the incitement to reduce inequality for cogent economic, not simply moral, reasons. It gives a clear answer as to why society should care about rising inequality.

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Tables

Table 1: Empirical Pareto Estimates

		US		UK	Australia	Italy
		1989	**2010**	**2007**	**2010**	**2010**
net worth	$\hat{\gamma}$	1.475	1.450	2.809	2.729	2.904
	$\hat{x}_{min}$	146,468	206,670	940,162	978,558	495,000
Hypothesis testing	PL	reject	reject	fail (98)	fail (92)	fail (98)
	Alt.	reject	reject	reject	reject	reject
financial assets	$\hat{\gamma}$	2.208	1.493	3.254	2.224	2.382
	$\hat{x}_{min}$	5,102,103	184,330	788,000	495,660	59,777
	PL	fail (60)	reject	fail (98)	fail (87)	fail (98)
	Alt.	reject	reject	reject	reject	reject
liabilities	$\hat{\gamma}$	1.988	2.036	3.086	3.571	3.393
	$\hat{x}_{min}$	158,376	217,700	147,000	554,457	109,900
	PL	fail (16)	fail (6)	fail (93)	fail (98)	fail (94)
	Alt.	reject	reject	reject	reject	reject

Sources: US: Survey of Consumer Finances (SCF); UK, Australia, Italy: Luxembourg Wealth Study (LWS)

Notes: Australian, Italian, UK and US data are all in local currency units. SCF (US only) financial asset data are the total market value of financial investments and products, deposit accounts, cash and other financial assets owned by household members, including pension assets as well as life insurance. LWS (GBR, AUS, ITA) financial asset data exclude pension assets and other long-term savings. Net worth data are total assets minus total liabilities, except Italy 2010, where disposable net worth is measured. Hypothesis testing: (PL) null hypothesis of fitted power-law distribution and generated power-law distribution (using estimated parameters) being the same, by Kolmogorov-Smirnov statistic; and (Alt.) null hypothesis of fitted alternative distribution and generated alternative distribution (using estimated parameters) being the same, by Kolmogorov-Smirnov statistic. Alternative distributions tested are an exponential distribution and log normal distribution, both with and without cutoff values ($\hat{x}_{min}$). If we fail to reject a null, the percentage of 2,500 simulated fittings of generated and fitted data which fail to reject null is reported in parentheses.

Table 2: Parameter calibration for static random network simulations

Variable	Values	Source(s)
c	$[0.05, 0.5]$	Author's estimates (Section A.2), Drehmann & Juselius (2012), BIS, FRB St. Louis
θ	$[0.8, 0.98]$	Elliott et al. (2014a)
β_i	$\underline{v}_i$	UScourts.gov (Federal Caseload Statistics)
λ	[0, 0.9]	
γ	[1.025, 2.375]	Author's estimates (Section 3.2), Elliott et al. (2014b)
d	[1, 2]	Blasques et al. (2015), Elliott et al. (2014b)

Table 3: Number of Crisis Episodes: 1870–2010, subsample 1

	Banking Crisis	Stock Market Crash	Both
Australia	0	4	0
Denmark	1	11	1
France	2	7	1
Italy	3	1	1
Netherlands	3	2	1
Spain	4	5	1
Sweden	1	12	1
United Kingdom	6	11	1
United States	13	24	7
Total	33	77	14
Likelihood of crisis (278 Obs)	0.119	0.277	0.050

Sources: Reinhart & Rogoff (2010)

Notes: Subsample is restricted to country-year observations with top1% wealth shares and aggregate wealth-income ratios.

Table 4: Number of Crisis Episodes: 1870–2010, subsample 2

	Banking Crisis	Stock Market Crash	Both
Australia	0	4	0
Denmark	0	2	0
France	0	5	0
Italy	3	1	1
Netherlands	0	1	0
Spain	4	5	1
Sweden	1	6	1
United Kingdom	6	10	1
United States	13	24	7
Total	27	58	11
Likelihood of crisis (213 Obs)	0.127	0.272	0.052

Sources: Reinhart & Rogoff (2010)

Notes: Subsample is restricted to country-year observations with top1% wealth shares, aggregate wealth-income ratios, and finance's share of total income.

Table 5: Summary statistics: Full Sample

Variable	Mean	Std. Dev.	Min.	Max.	Obs	Countries
Top 1% Shr Net Worth	0.275	0.126	0.063	0.690	401	13
Wealth-Income ratio	4.59	1.421	1.805	8.855	1,174	12
Finance Shr of Income	0.036	0.02	0.001	0.124	1,402	15
$\tilde{r}$	0.001	0.117	-1.415	0.799	731	15
$\hat{g}$	0.018	0.052	-0.509	0.659	2,702	15
Private Sector Credit	0.724	0.404	0.114	2.022	813	15
Top Marginal Tax Rate	58.366	20.704	2	97.5	714	10

Notes: The full sample includes all observations on all available countries for a given variable, thus exceeding the number of countries in each of our sub-samples.

Table 6: Summary statistics: Subsample 1

Variable	Mean	Std. Dev.	Min.	Max.	Obs	Countries
Top 1% Shr Net Worth	0.269	0.125	0.063	0.690	278	9
Wealth-Income ratio	4.168	1.019	2.258	8.855	278	9

Notes: Subsample 1 is restricted to country-year observations with top1% wealth shares and aggregate wealth-income ratios.

Table 7: Summary statistics: Subsample 2

Variable	Mean	Std. Dev.	Min.	Max.	Obs	Countries
Top 1% Shr Net Worth	0.246	0.12	0.063	0.690	213	9
Wealth-Income ratio	4.195	0.985	2.258	8.855	213	9
Finance Shr of Income	0.047	0.011	0.011	0.079	213	9

Notes: Subsample 2 is restricted to country-year observations with top1% wealth shares, aggregate wealth-income ratios, and finance's share of total income.

Table 8: Summary statistics: Subsample 3

Variable	Mean	Std. Dev.	Min.	Max.	Obs	Countries
Top 1% Shr Net Worth	0.205	0.079	0.063	0.453	156	9
Wealth-Income ratio	4.12	0.812	2.262	7.714	156	9
Finance Shr of Income	0.049	0.01	0.026	0.077	156	9
$\tilde{r}$	-0.002	0.097	-0.379	0.325	156	9
$\hat{g}$	0.024	0.019	-0.028	0.065	156	9

Notes: Subsample 3 is restricted to country-year observations with top1% wealth shares, aggregate wealth-income ratios, finance's share of total income, and $r - g$.

Table 9: Summary statistics: Subsample 4

Variable	Mean	Std. Dev.	Min.	Max.	Obs	Countries
Top 1% Shr Net Worth	0.206	0.082	0.063	0.453	134	6
Wealth-Income ratio	4.028	0.724	2.262	5.864	134	6
Finance Shr of Income	0.049	0.01	0.026	0.077	134	6
$\tilde{r}$	-0.006	0.097	-0.379	0.325	134	6
$\hat{g}$	0.024	0.019	-0.028	0.065	134	6
Private Sector Credit	0.697	0.411	0.114	1.719	134	6
Top Marginal Tax Rate	61.987	18.234	28	97.5	134	6

Notes: Subsample 4 is restricted to country-year observations with the same set of variables in the the full sample, Table 5.

Table 10: Likelihood of Banking Crisis

	(1)	(2)	(3)	(4)
Top 1% Shr Net Worth $_{t-2}$	-0.467	-2.615	-2.500	-2.548
	(2.857)	(2.447)	(2.167)	(2.146)
Wealth-Income ratio $_{t-2}$	0.032	-0.187	-0.003	-0.159
	(0.238)	(0.191)	(0.310)	(0.374)
Top 1% Shr Net Worth $\times$ Wealth-Income ratio $_{t-2}$	0.434	1.845**	0.885	1.745
	(0.913)	(0.583)	(1.232)	(1.193)
Finance Shr of Income $_{t-2}$		-0.640	-23.927	-16.234
		(12.730)	(18.649)	(20.865)
Top 1% Shr Net Worth $\times$ Finance Shr of Income $_{t-2}$		-28.309	78.910	39.274
		(50.218)	(94.065)	(107.573)
$\tilde{r}$ $_{t-2}$			0.025	0.088
			(0.224)	(0.202)
$\hat{g}$ $_{t-2}$			1.285	-0.011
			(0.979)	(1.015)
Private Sector Credit $_{t-2}$				0.067
				(0.112)
Top Marginal Tax Rate $_{t-2}$				-0.006**
				(0.002)
AIC	-31.5	-18.9	-4.7	-10.5
R^2	0.545	0.572	0.531	0.566
Countries	9	9	9	6
Obs	273	213	156	134

Clustered standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable is a binary indicator of crisis type for given country and year. Linear probability model is estimated with two-way fixed effects (2FE), controlling for country and year. A proxy for the rate of return on capital, $\tilde{r}$ is the difference in first-differences of financial development (the sum of all bank deposits and stock market capitalization as a percentage of GDP). The variable $\hat{g}$, a proxy for growth, is the annual percentage change in GDP per capita. Private sector credit is measured as a share of GDP and the top marginal tax rate is a percentage.

Table 11: Likelihood of Stock Market Crash

	(1)	(2)	(3)	(4)
Top 1% Shr Net Worth $_{t-2}$	-3.425*	-8.616***	-8.863***	-9.591**
	(1.757)	(1.359)	(1.841)	(2.929)
Wealth-Income ratio $_{t-2}$	-0.323*	-0.570***	-0.608***	-0.760*
	(0.150)	(0.081)	(0.170)	(0.303)
Top 1% Shr Net Worth $\times$ Wealth-Income ratio $_{t-2}$	1.129*	2.306***	2.675***	2.844*
	(0.571)	(0.272)	(0.745)	(1.160)
Finance Shr of Income $_{t-2}$		-0.648	7.439	6.226
		(10.751)	(14.304)	(25.797)
Top 1% Shr Net Worth $\times$ Finance Shr of Income $_{t-2}$		50.426	9.883	6.643
		(46.507)	(65.964)	(118.576)
$\tilde{r}$ $_{t-2}$			-0.387**	-0.371
			(0.162)	(0.205)
$\hat{g}$ $_{t-2}$			0.005	-0.687
			(1.394)	(1.720)
Private Sector Credit $_{t-2}$				0.063
				(0.146)
Top Marginal Tax Rate $_{t-2}$				-0.003
				(0.008)
AIC	-22.4	-102.9	-53.1	-65.4
R^2	0.742	0.826	0.772	0.794
Countries	9	9	9	6
Obs	273	213	156	134

Clustered standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable is a binary indicator of crisis type for given country and year. Linear probability model is estimated with two-way fixed effects (2FE), controlling for country and year. A proxy for the rate of return on capital, $\tilde{r}$ is the difference in first-differences of financial development (the sum of all bank deposits and stock market capitalization as a percentage of GDP). The variable $\hat{g}$, a proxy for growth, is the annual percentage change in GDP per capita. Private sector credit is measured as a share of GDP and the top marginal tax rate is a percentage.

Table 12: Likelihood of Financial Crisis

	Banking Crisis	Stock Market Crash	Both
Top 1% Shr Net Worth $_{t-2}$	-4.181	-8.333***	-6.376***
	(2.266)	(1.599)	(1.260)
Wealth-Income ratio $_{t-2}$	-0.650*	-0.487**	-0.750***
	(0.311)	(0.200)	(0.191)
Wealth-Income ratio ^{2} $_{t-2}$	0.033*	-0.006	0.015
	(0.015)	(0.011)	(0.010)
Top 1% Shr Net Worth × Wealth-Income ratio $_{t-2}$	2.150***	2.251***	2.590***
	(0.604)	(0.297)	(0.521)
Finance Shr of Income $_{t-2}$	-2.846	-0.250	9.769
	(10.517)	(10.490)	(9.428)
Top 1% Shr Net Worth × Finance Shr of Income $_{t-2}$	-29.286	50.602	-36.490
	(43.097)	(45.572)	(47.667)
AIC	-24.5	-103.2	-190.8
R^2	0.583	0.826	0.519
Countries	9	9	9
Obs	213	213	213

Clustered standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable is a binary indicator if a type of financial crisis occurs for a given country and year. Linear probability model is estimated with two-way fixed effects (2FE), controlling for country and year.

Appendix

A.1 Failure Algorithm

This algorithm is used the determine the ordering of individuals who fail financially in the event of an initial income shock. It finds what Elliott et al. (2014a) refer to as the *best-case* equilibrium, i.e. there exist the fewest number of failures and highest values $v_{i,t}$ possible.

The initial financial shock occurs at period $t = 0$, changing real asset price values to $\tilde{\mathbf{p}}$. Let Z_t represent the set of financially failed individuals at period t, where $Z_0 = \emptyset$. Then for periods $t \geqslant 1$:

Step 1 Let $\mathbf{b}_{t-1}$ be a vector of failure costs with element $b_{i,t-1} = \beta_i$ if $i \in Z_{t-1}$ and 0 otherwise. By definition, $\beta_i = 0 \; \forall \; i$ at $t = 1$.

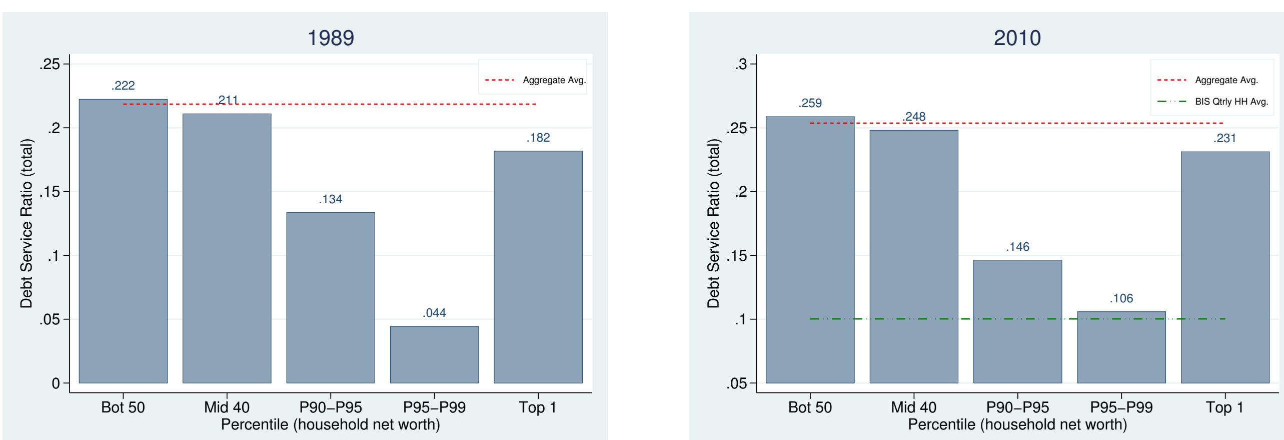
Step 2 Let Z_t be the set of all j where $v_{j,t} < 0$ and:

$$\mathbf{v_t} = \mathbf{A}(\mathbf{D}\tilde{\mathbf{p}} - \mathbf{b_{t-1}}) - \underline{\mathbf{v}}.$$

Step 3 Stop iterations if $Z_t = Z_{t-1}$, otherwise return to Step 1.

The resulting set Z_T, at terminal period T, is the corresponding set of individuals who have failed financially. An important feature is that the individuals added each period $(Z_t - Z_{t-1})$ are those individuals whose financial failures were catalyzed by the preceding set of cumulative failures. For example, Z_1 is the first group of individuals to fail and Z_2 includes the group of individuals who fail in the second period as a direct result of the individuals failing during period $t = 1$.

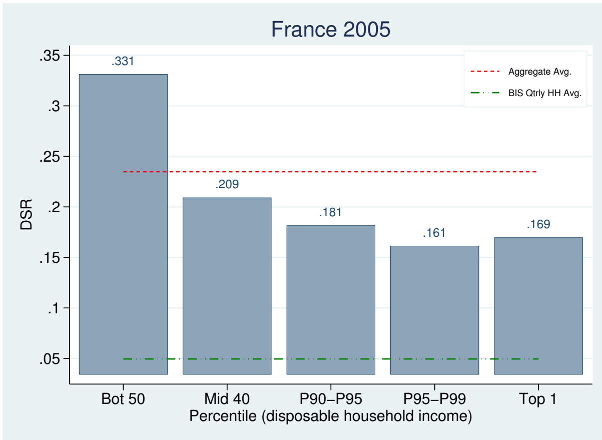
A.2 Distributions of Household Debt Service Ratio (DSR)



SOURCE: Survey of Consumer Finances (SCF)

SOURCE: Survey of Consumer Finances (SCF)

Figure A.2.1: US: 1989, 2010



SOURCE: Luxembourg Income Study (LIS)

Figure A.2.2: FRANCE: 2005

A.3 Additional Parameterizations

A.3.1 Changes in parameter c

The parameter c determines the share of each node's value that can be securitized and claimed by other nodes. It measures the share of a node's cash flows that are sent to creditor nodes, an approximation of the level of financialization in the network at the intensive margin. Simulation results of the static random network for values of $c = \{0.1, 0.2, 0.3, 0.4, 0.6, 0.8\}$, and $\theta = 0.92$ and $\lambda = 0$, are shown in Figure A.3.1.

When $c = 0.1$, less than seven percent of the nodes fail under all levels of wealth inequality and aggregate wealth. Only as the share of individual wealth that can be claimed increases ($c \geqslant 0.2$) does the positive effect of wealth inequality on S begin to assert itself at moderate levels of wealth ($d \in [1.4, 1.6]$). As financialization at the intensive margin, c, continues increasing instability at the highest levels of aggregate wealth keeps increasing until we reach a maximum amount of contagion at approximately $c = 0.6$. (See Figure A.3.1.) Hereafter, instability declines as c increases. Thus the inverted U-shaped effect of financialization (at the extensive margin) on instability observed from increasing network wealth (d) appears to also take shape when financialization at the intensive margin (c) is also increased—though the downward sloping portion occurs at values of c that are well beyond any reasonably estimated debt servicing burden, commercial or private. These results broadly echo those of Drehmann & Juselius (2012) who show debt service burdens positively predict economic downturns.

A.3.2 Changes in parameter θ

The parameter θ determines the financial robustness of an individual node in the event of an income shock. Since financial failure is predicated on $v_i < \underline{v}_i$ and $\underline{v}_i = \theta v_i$, the smaller θ is the more financially robust an individual is. An individual's financial fragility is increasing in θ. Simulation results of the static random network for values of $\theta = \{0.8, 0.84, 0.88, 0.92, 0.94, 0.98\}$, and $c = 0.3$ and $\lambda = 0$, are shown in Figure A.3.2.

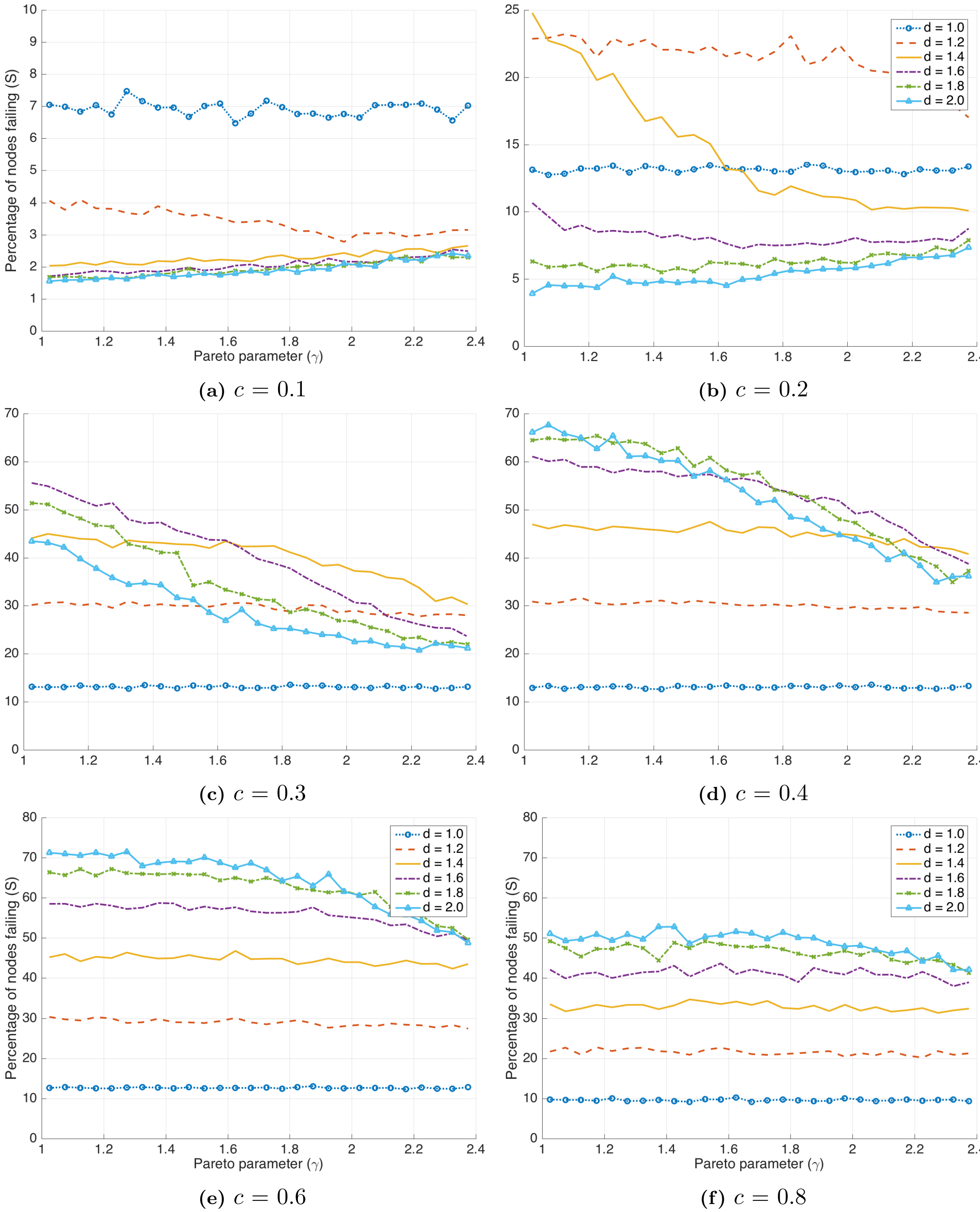
As θ increases an individual is more likely to breach $\underline{v}_i$ in the event that they personally experience an income shock or absorb failures indirectly through the dependency matrix $\mathbf{A}$. When θ is smallest (0.8), individuals are especially robust to any shock and the share of failing nodes is very low ($S < 2\%$). See Figure A.3.2. When θ increases (0.88) individual financial vulnerability increases, but contagion is still very low and unaffected by inequality. When θ is high ($\geqslant 0.92$), only a slight disturbance can tip an individual into financial failure and contagion spreads easily. The impact of wealth inequality on contagion is also strongly felt, but, again, is dependent on the network's aggregate wealth level.

A.3.3 Changes in parameter λ

The parameter λ determines the magnitude of the random income shock imposed on a single node. An income shock decreases the market price of the node's real asset to $\tilde{p}_k = \lambda p_k$, where $p_k = 1$ and $\lambda \in [0, 1)$. Therefore as the magnitude of the income shock is decreasing in λ. Simulation results of the static random network for values of $\lambda = \{0, 0.25, 0.5, 0.75, 0.9\}$, and $c = 0.3$ and $\theta = 0.92$, are shown in Figure A.3.3.

Only when λ is very close to θ in value (0.9) is there any significant decrease in contagion. If $\lambda < \theta$, no matter the size of the shock the overall pattern of our simulation results holds: increasing inequality causes an increase in the percentage of nodes failing, conditional on a certain level of aggregate wealth; and increasing the aggregate wealth of the network, first increases then decreases network stability.[58]

[58] We test one counterfactual simulation in which a random individual receives a positive income shock, setting $\lambda = 2$. Because contagion is a property of net worth decreasing below some threshold value, we expect increases in net worth to have no effect on contagion. As our model would predict, the network is perfectly stable and no financial failures occur at any level of aggregate wealth. Contagion is conditional upon some negative shock.



(a) $c = 0.1$

(b) $c = 0.2$

(c) $c = 0.3$

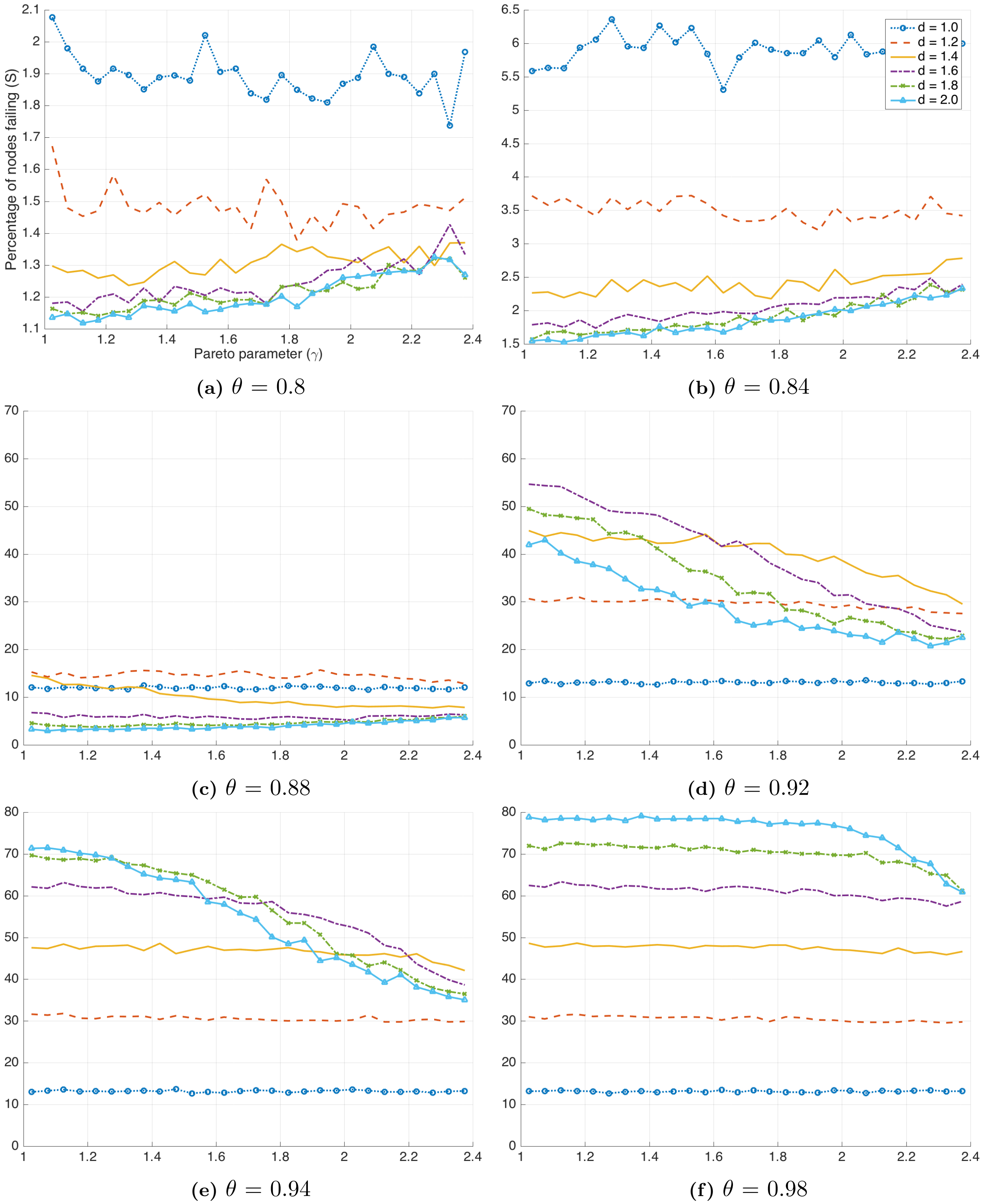
(d) $c = 0.4$

(e) $c = 0.6$

(f) $c = 0.8$

Figure A.3.1: Changes in parameter c

Notes: Pareto distributed in-degree d. Aggregate wealth is increasing in expected in-degree d. $\theta = 0.92$ and $\lambda = 0$. As γ increases wealth inequality decreases. The domain of $\gamma = [1.025, 2.375]$ corresponds to Gini coefficients of [0.952, 0.267] and top 1% wealth shares of [0.894, 0.070]. Percentage of financial failures is average of 1,000 simulations.



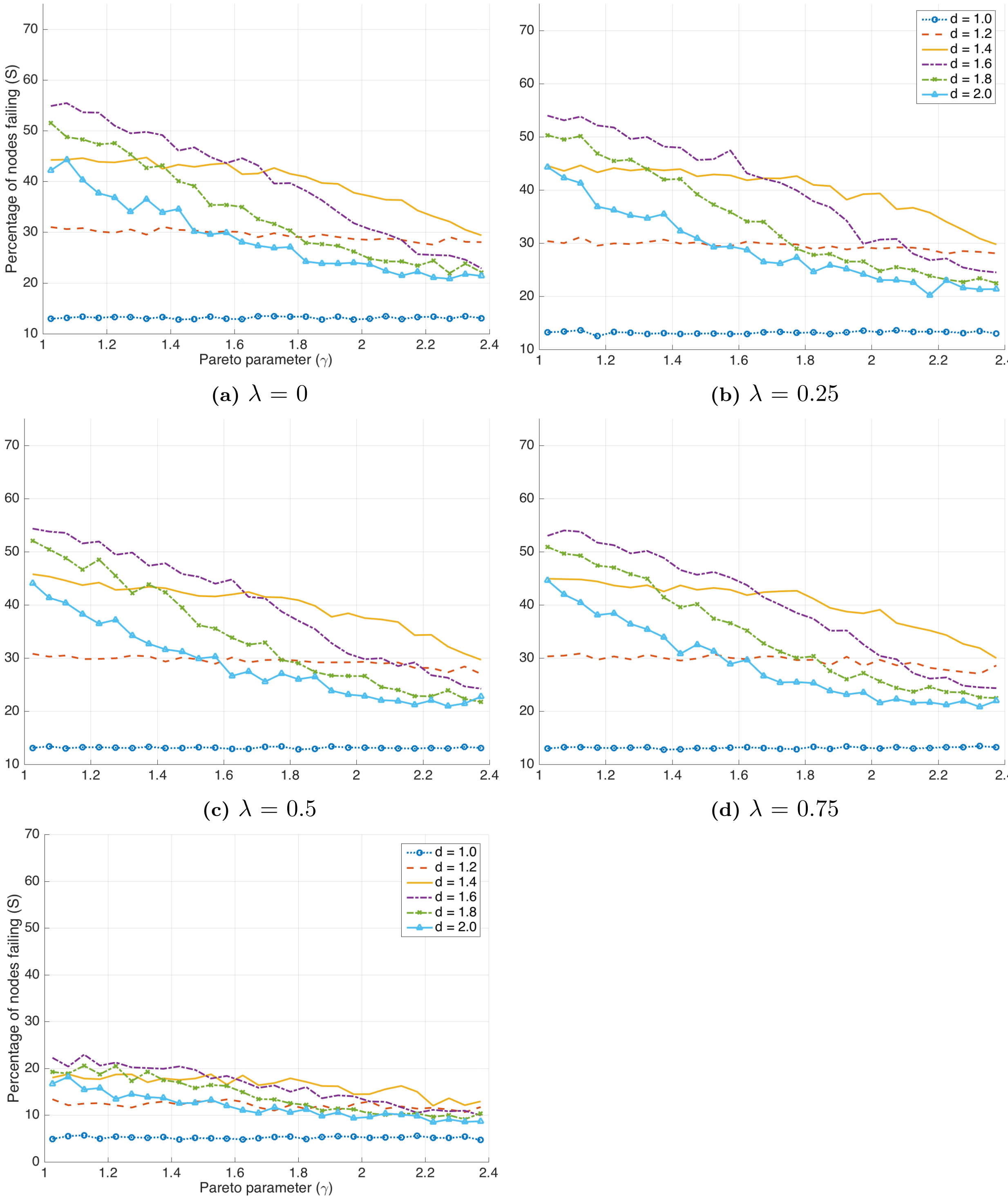
(a) $\theta = 0.8$ **(b)** $\theta = 0.84$

(c) $\theta = 0.88$ **(d)** $\theta = 0.92$

(e) $\theta = 0.94$ **(f)** $\theta = 0.98$

Figure A.3.2: Changes in parameter θ

Notes: Pareto distributed in-degree d. Aggregate wealth is increasing in expected in-degree d. $c = 0.3$ and $\lambda = 0$. As γ increases wealth inequality decreases. The domain of $\gamma = [1.025, 2.375]$ corresponds to Gini coefficients of [0.952, 0.267] and top 1% wealth shares of [0.894, 0.070]. Percentage of financial failures is average of 1,000 simulations.



(a) $\lambda = 0$

(b) $\lambda = 0.25$

(c) $\lambda = 0.5$

(d) $\lambda = 0.75$

(e) $\lambda = 0.9$

Figure A.3.3: Changes in parameter λ.

Notes: Pareto distributed in-degree d. Aggregate wealth is increasing in expected in-degree d. $c = 0.3$ and $\theta = 0.92$. As γ increases wealth inequality decreases. The domain of $\gamma = [1.025, 2.375]$ corresponds to Gini coefficients of [0.952, 0.267] and top 1% wealth shares of [0.894, 0.070]. Percentage of financial failures is average of 1,000 simulations.

A.4 Data

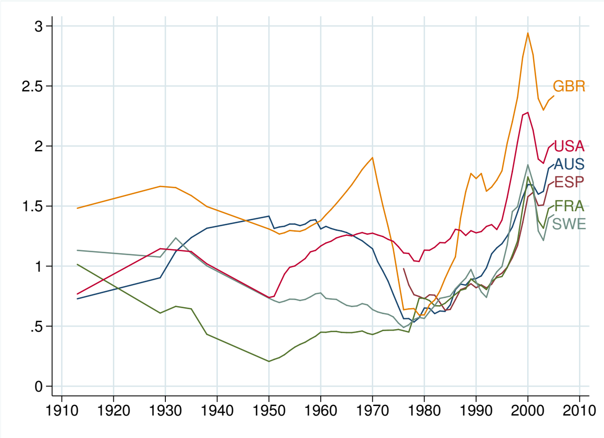


Figure A.4.1: Financial Development (% GDP)

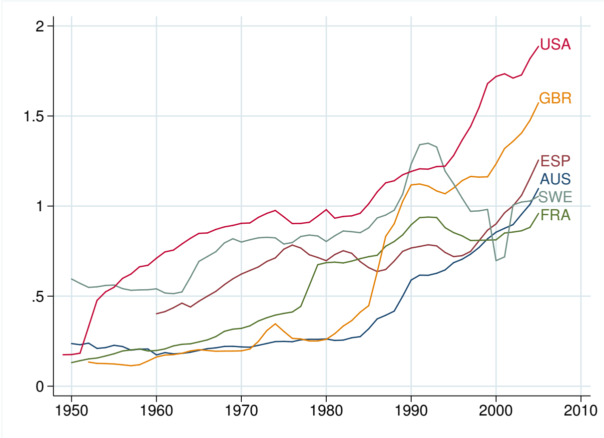


Figure A.4.2: Private Sector Credit (% GDP)

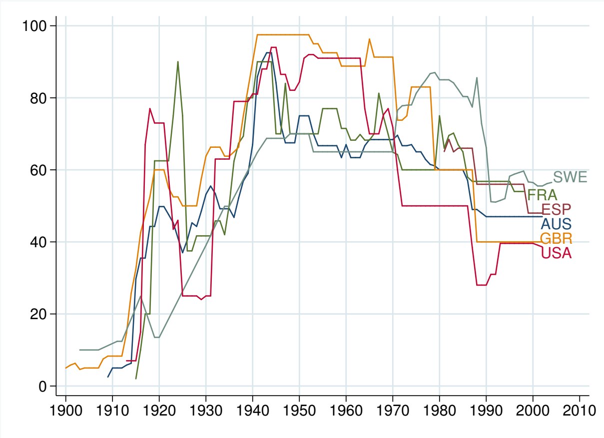


Figure A.4.3: Top Marginal Tax Rates (%)

A.5 Additional Regression Results

Additional Crisis Regressors

Table A.5.1: 5 Year Averages: Likelihood of Banking Crisis

	(1)	(2)	(3)	(4)
Top 1% Shr Net Worth	-2.203	-2.915	-0.626	-9.915***
	(3.058)	(3.424)	(3.619)	(2.359)
Wealth-Income ratio	-0.115	-0.100	-0.101	-1.241*
	(0.290)	(0.298)	(0.454)	(0.498)
Top 1% Shr Net Worth × Wealth-Income ratio	0.876	0.823	0.734	5.432***
	(1.029)	(1.047)	(1.846)	(0.852)
Finance Shr of Income	-1.001	-4.433	-4.350	13.062
	(2.703)	(5.038)	(10.349)	(17.382)
Top 1% Shr Net Worth × Finance Shr of Income		21.874	-5.074	-75.985
		(40.351)	(76.635)	(117.799)
$\tilde{r}$			2.305	3.727
			(1.732)	(2.426)
$\hat{g}$			-5.821	-3.123
			(6.450)	(5.684)
Private Sector Credit				0.106
				(0.264)
Top Marginal Tax Rate				-0.013*
				(0.006)
AIC	-21.7	-21.9	-12.4	-33.3
R^2	0.366	0.368	0.361	0.601
Countries	9	9	9	6
Obs	72	72	59	45

Clustered standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: All variables are averaged over 5 year intervals. Dependent variable is 5 year average of a binary indicator of crisis type for given country and year. Linear probability model is estimated with two-way fixed effects (2FE), controlling for country and year. Financial development is the sum of all bank deposits and stock market capitalization as a percentage of GDP, and a proxy for the rate of return on capital, r. A second proxy, $\tilde{r}$ is the difference in first-differences of financial development. The variable $\hat{g}$, a proxy for growth, is the annual percentage change in GDP per capita. Private sector credit is measured as a share of GDP and the top marginal tax rate is a percentage.

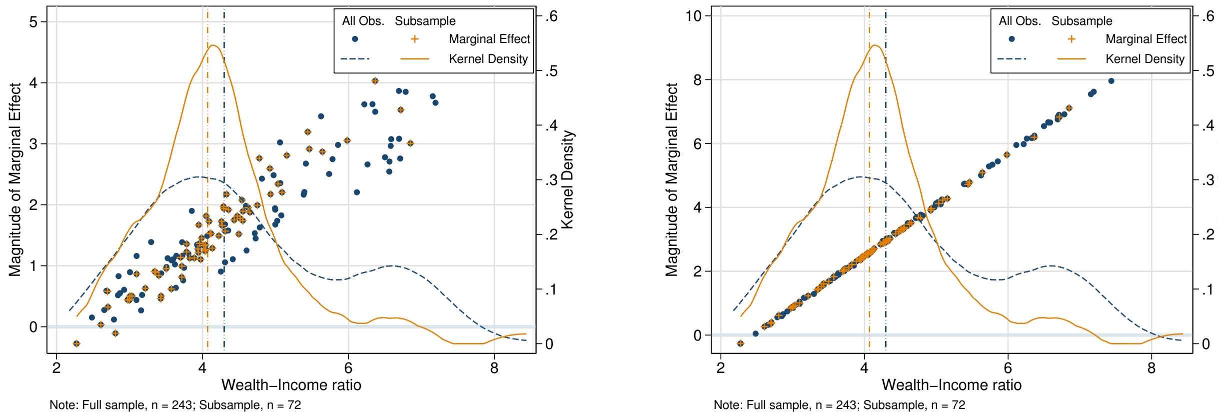
Table A.5.2: 5 Year Averages: Likelihood of Stock Market Crash

	(1)	(2)	(3)	(4)
Top 1% Shr Net Worth	-3.900	-3.829	-4.549	-4.037
	(2.107)	(2.660)	(2.487)	(2.538)
Wealth-Income ratio	-0.327	-0.329	-0.375	-0.228
	(0.182)	(0.182)	(0.289)	(0.363)
Top 1% Shr Net Worth × Wealth-Income ratio	1.595*	1.601**	1.831	0.907
	(0.698)	(0.693)	(1.242)	(1.165)
Finance Shr of Income	-2.996	-2.653	-0.763	-10.279
	(3.243)	(6.591)	(6.855)	(12.239)
Top 1% Shr Net Worth × Finance Shr of Income		-2.185	-2.485	36.141
		(37.610)	(64.430)	(81.038)
$\tilde{r}$			-2.007	-4.600
			(2.032)	(3.539)
$\hat{g}$			0.618	-9.404
			(5.526)	(9.478)
Private Sector Credit				-0.179
				(0.293)
Top Marginal Tax Rate				-0.005
				(0.004)
AIC	-67.7	-67.7	-45.5	-41.9
R^2	0.738	0.738	0.674	0.710
Countries	9	9	9	6
Obs	72	72	59	45

Clustered standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: All variables are averaged over 5 year intervals. Dependent variable is 5 year average of a binary indicator of crisis type for given country and year. Linear probability model is estimated with two-way fixed effects (2FE), controlling for country and year. Financial development is the sum of all bank deposits and stock market capitalization as a percentage of GDP, and a proxy for the rate of return on capital, r. A second proxy, $\tilde{r}$ is the difference in first-differences of financial development. The variable $\hat{g}$, a proxy for growth, is the annual percentage change in GDP per capita. Private sector credit is measured as a share of GDP and the top marginal tax rate is a percentage.

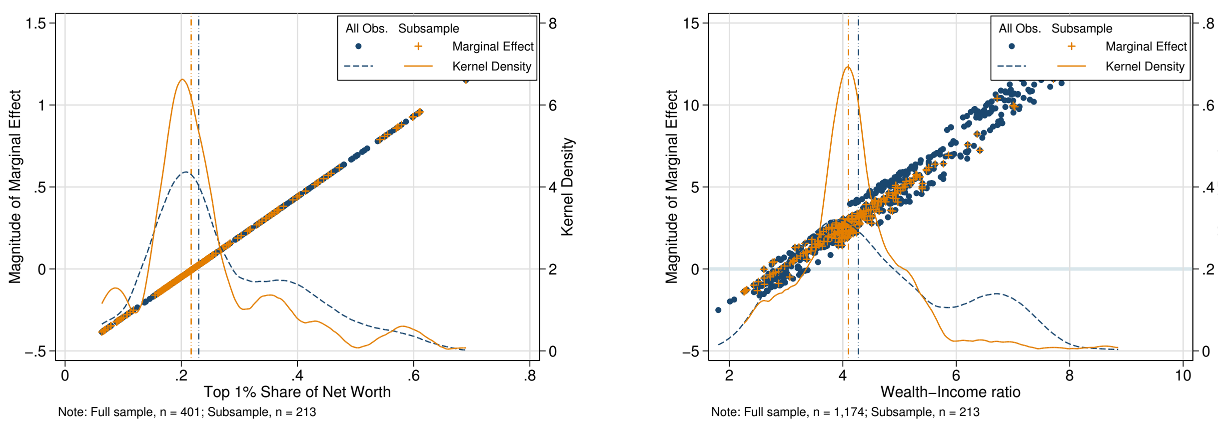


(a) Banking Crises

(b) Stock Market Crashes

Figure A.5.1: Marginal Effect of Wealth Inequality on Likelihood of Financial Crisis: 5 Year Averages

Notes: Based on model specification (2) in Tables A.5.1 and A.5.2.



(a) Aggregate Wealth

(b) Wealth Inequality

Figure A.5.2: Marginal Effects on Likelihood of Both Crises

Notes: Based on model specification (2) in Table A.5.3.

Table A.5.3: LIKELIHOOD OF *Both* BANKING CRISIS AND STOCK MARKET CRASH

	(1)	(2)	(3)	(4)
Top 1% Shr Net Worth $_{t-2}$	-4.412***	-5.666***	-4.770**	-3.831
	(1.297)	(1.524)	(1.594)	(2.171)
Wealth-Income ratio $_{t-2}$	-0.353**	-0.540***	-0.347	-0.369
	(0.107)	(0.110)	(0.203)	(0.225)
Top 1% Shr Net Worth $\times$ Wealth-Income ratio $_{t-2}$	1.481***	2.452***	1.537	1.935
	(0.437)	(0.489)	(0.926)	(1.024)
Finance Shr of Income $_{t-2}$		10.769	-5.062	6.642
		(10.465)	(9.589)	(4.835)
Top 1% Shr Net Worth $\times$ Finance Shr of Income $_{t-2}$		-36.047	39.336	0.004
		(50.962)	(49.393)	(30.493)
$\tilde{r}_{\ t-2}$			-0.085	-0.264
			(0.244)	(0.406)
$\hat{g}_{\ t-2}$			-0.630	-1.666
			(1.474)	(2.066)
Private Sector Credit $_{t-2}$				-0.168
				(0.084)
Top Marginal Tax Rate $_{t-2}$				-0.008*
				(0.003)
AIC	-247.5	-188.2	-146.9	-131.4
R^2	0.507	0.514	0.409	0.406
Countries	9	9	9	6
Obs	277	213	156	134

Clustered standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

NOTES: The dependent variable is a binary indicator equal to one if either banking crisis or stock market crash occur for a given country, year observation. Linear probability model is estimated with two-way fixed effects (2FE), controlling for country and year. A proxy for the rate of return on capital, $\tilde{r}$ is the difference in first-differences of financial development (the sum of all bank deposits and stock market capitalization as a percentage of GDP). The variable $\hat{g}$, a proxy for growth, is the annual percentage change in GDP per capita. Private sector credit is measured as a share of GDP and the top marginal tax rate is a percentage.

A.6 Robustness Checks

Fixed Effect Logit Estimation

Table A.6.1: Fixed Effect Logit: Likelihood of Banking Crisis

	(1)	(2)	(3)	(4)
Top 1% Shr Net Worth $_{t-2}$	3.322	-6.966	-42.786	-75.463*
	(5.970)	(8.851)	(32.020)	(43.574)
Wealth-Income ratio $_{t-2}$	0.769*	0.126	-2.827	-5.696**
	(0.457)	(0.495)	(2.052)	(2.884)
Top 1% Shr Net Worth × Wealth-Income ratio $_{t-2}$	-0.927	1.111	10.772	22.956*
	(1.264)	(1.626)	(9.182)	(12.134)
Finance Shr of Income $_{t-2}$		34.281	22.723	-1.471
		(20.941)	(28.316)	(42.871)
$\tilde{r}$ $_{t-2}$			-1.104	-0.861
			(2.735)	(2.823)
$\hat{g}$ $_{t-2}$			-12.478	-13.896
			(13.092)	(13.916)
Private Sector Credit $_{t-2}$				-1.788
				(1.554)
Top Marginal Tax Rate $_{t-2}$				-0.068**
				(0.031)
AIC	172.3	140.5	102.3	94.3
Pseudo-R^2	0.035	0.072	0.055	0.116
Countries	9	7	6	5
Obs	273	201	141	130

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is a binary indicator equal to one if a crisis occurs for a country in a given year. Fixed effect logit model is estimated with country fixed effects. Coefficient estimates are reported. A proxy for the rate of return on capital, $\tilde{r}$ is the difference in first-differences of financial development (the sum of all bank deposits and stock market capitalization as a percentage of GDP). The variable $\hat{g}$, a proxy for growth, is the annual percentage change in GDP per capita. Private sector credit is measured as a share of GDP and the top marginal tax rate is a percentage.

Table A.6.2: Fixed Effect Logit: Likelihood of Stock Market Crash

	(1)	(2)	(3)	(4)
Top 1% Shr Net Worth $_{t-2}$	2.666	-0.403	-154.573***	-118.591**
	(4.259)	(6.036)	(50.103)	(53.712)
Wealth-Income ratio $_{t-2}$	0.256	-0.246	-9.227***	-6.990**
	(0.379)	(0.501)	(2.751)	(2.939)
Top 1% Shr Net Worth $\times$ Wealth-Income ratio $_{t-2}$	-0.113	1.505	46.240***	36.959***
	(0.947)	(1.495)	(13.410)	(14.330)
Finance Shr of Income $_{t-2}$		21.232	36.716	33.731
		(16.587)	(26.872)	(38.773)
$\tilde{r}$ $_{t-2}$			-2.379	-1.370
			(2.226)	(2.341)
$\hat{g}$ $_{t-2}$			12.543	8.275
			(12.778)	(13.401)
Private Sector Credit $_{t-2}$				-0.199
				(1.784)
Top Marginal Tax Rate $_{t-2}$				-0.005
				(0.025)
AIC	287.4	212.0	118.6	112.2
Pseudo-R^2	0.018	0.054	0.197	0.166
Countries	9	9	9	6
Obs	273	213	156	134

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is a binary indicator equal to one if a crisis occurs for a country in a given year. Fixed effect logit model is estimated with country fixed effects. Coefficient estimates are reported. A proxy for the rate of return on capital, $\tilde{r}$ is the difference in first-differences of financial development (the sum of all bank deposits and stock market capitalization as a percentage of GDP). The variable $\hat{g}$, a proxy for growth, is the annual percentage change in GDP per capita. Private sector credit is measured as a share of GDP and the top marginal tax rate is a percentage.

Income Inequality Data

Table A.6.3: Likelihood of Banking Crisis with Income Inequality

	(1)	(2)	(3)	(4)
Top 1% Shr Income $_{t-2}$	3.000	-2.336	6.362	20.889
	(2.085)	(10.277)	(8.704)	(12.336)
Wealth-Income ratio $_{t-2}$	0.128	-0.088	0.025	0.046
	(0.088)	(0.135)	(0.104)	(0.184)
Top 1% Shr Income × Wealth-Income ratio $_{t-2}$	-0.374	2.525	0.953	-0.136
	(0.503)	(1.621)	(1.520)	(1.926)
Finance Shr of Income $_{t-2}$		-3.692	1.188	15.632
		(9.899)	(7.839)	(11.752)
Top 1% Shr Income × Finance Shr of Income $_{t-2}$		-76.192	-110.912	-328.468***
		(116.445)	(96.938)	(61.937)
$\tilde{r}$ $_{t-2}$			-0.297*	-0.578***
			(0.149)	(0.152)
$\hat{g}$ $_{t-2}$			-2.115	-3.185
			(2.127)	(1.692)
Private Sector Credit $_{t-2}$				0.698***
				(0.141)
Top Marginal Tax Rate $_{t-2}$				-0.010**
				(0.004)
AIC	96.9	114.7	103.1	45.2
R^2	0.393	0.342	0.247	0.267
Countries	10	10	10	8
Obs	538	393	335	271

Clustered standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable is a binary indicator of crisis type for given country and year. Linear probability model is estimated with two-way fixed effects (2FE), controlling for country and year. A proxy for the rate of return on capital, $\tilde{r}$ is the difference in first-differences of financial development (the sum of all bank deposits and stock market capitalization as a percentage of GDP). The variable $\hat{g}$, a proxy for growth, is the annual percentage change in GDP per capita. Private sector credit is measured as a share of GDP and the top marginal tax rate is a percentage.

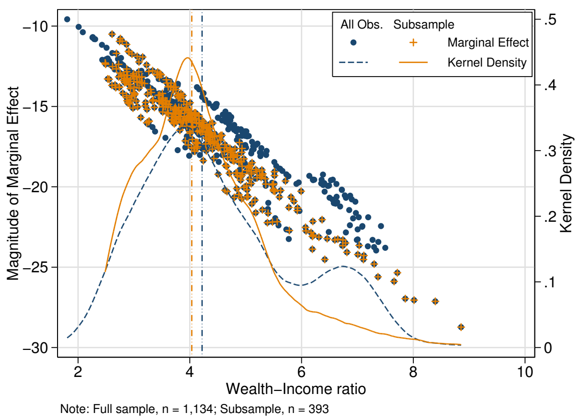
Table A.6.4: Likelihood of Stock Market Crash with Income Inequality

	(1)	(2)	(3)	(4)
Top 1% Shr Income $_{t-2}$	0.279	1.449	-0.792	0.766
	(1.250)	(6.999)	(8.380)	(19.621)
Wealth-Income ratio $_{t-2}$	0.039	-0.016	-0.048	-0.048
	(0.058)	(0.102)	(0.130)	(0.231)
Top 1% Shr Income × Wealth-Income ratio $_{t-2}$	-0.082	0.528	1.409	2.171
	(0.321)	(1.434)	(1.882)	(2.806)
Finance Shr of Income $_{t-2}$		3.180	4.983	3.904
		(9.044)	(11.898)	(22.051)
Top 1% Shr Income × Finance Shr of Income $_{t-2}$		-61.930	-92.118	-149.300
		(120.830)	(148.670)	(302.752)
$\tilde{r}$ $_{t-2}$			-0.071	-0.231
			(0.198)	(0.293)
$\hat{g}$ $_{t-2}$			1.242	0.419
			(1.429)	(1.619)
Private Sector Credit $_{t-2}$				0.035
				(0.263)
Top Marginal Tax Rate $_{t-2}$				-0.001
				(0.007)
AIC	233.1	165.6	184.8	154.2
R^2	0.528	0.539	0.453	0.418
Countries	10	10	10	8
Obs	538	393	335	271

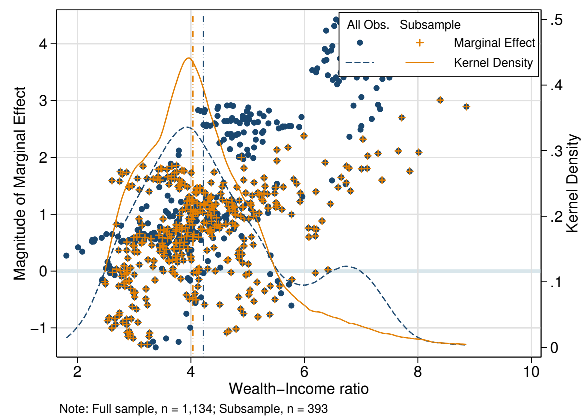
Clustered standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable is a binary indicator of crisis type for given country and year. Linear probability model is estimated with two-way fixed effects (2FE), controlling for country and year. A proxy for the rate of return on capital, $\tilde{r}$ is the difference in first-differences of financial development (the sum of all bank deposits and stock market capitalization as a percentage of GDP). The variable $\hat{g}$, a proxy for growth, is the annual percentage change in GDP per capita. Private sector credit is measured as a share of GDP and the top marginal tax rate is a percentage.



(a) Banking Crises



(b) Stock Market Crashes

Figure A.6.1: Marginal Effect of Income Inequality on Likelihood of Financial Crisis