Aggregate Wealth and Its Distribution as Determinants of Financial Crises

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Abstract

This paper investigates the relationship between wealth inequality and financial crises. While substantiation of a role for income inequality is ambiguous in the literature, we present evidence suggesting a unique capacity for the accumulation of assets on the likelihood of a financial crisis episode. Testing 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, has a significantly positive and increasing marginal effect on the likelihood of financial crises, particularly stock market crashes. Predicted probabilities closely track the incidence of financial crises in the United States and United Kingdom over the past century. We argue these results reveal an important role for the distribution of accumulated assets in the macro-financial stability of rich countries. The distribution of stocks may capture structural vulnerabilities that the distribution of flows cannot expose. An economic network hypothesis is proposed for interpreting these results.

Keywords: Financial crisis, growth and fluctuations, income inequality, wealth inequality

JEL-Classification: D31, E22, G01, G17, N10

1 Introduction

Familiar plots from Thomas Piketty and Emmanuel Saez[1] display the share of income held by top percentiles in the United States provocatively peaking before both the Great Crash and the more recent global financial crisis. This correlation has generated a host of discussions and research into the relationship between income inequality and financial crisis. (See Krugman (2010), Acemoglu (2011), and Bordo & Meissner (2012), among others.)

There exist two primary mechanisms in the literature to explain the apparent association between inequality and financial crisis. The first, and less-cited, is the institutional narrative, favored by Acemoglu and also Moss (2009), whereby deregulatory shifts unleashed market forces that increased risk, leverage, and economic fallout in the event of a crash.

The second proposed mechanism is a household debt story. One variation emphasizes a non-rich household dynamic, such that income inequality pushed households to borrow while holding consumption and savings constant (Cynamon & Fazzari (2014), Carvalho & Di Guilmi (2014)). Another variation places the emphasis on the supply side—not unlike the institutional story. Government agencies loosened the reigns for household lending and homeownership (Rajan (2011)) or the federal reserve held interest rates down (Stiglitz (2012)) in an effort to stimulate aggregate demand. Yet another variation points to wealthy high-net-worth individuals who sought safe, high-yielding investments in a world of declining interest rates. The mass of collateralized debt obligations and asset-backed securities was a response to the insatiable investing appetites of hedge funds and other institutional investors abroad (Lysandrou (2011), Stockhammer (2012), Stockhammer (2015)). Still others (Kumhof & Ranciere (2010) argued that the precise causal force of growing debt was less concerning since many forces contributed (e.g. weakened labor bargaining positions, stunted income growth, and the search for yield amongst wealthy households). What mattered was the equilibrium level of household debt, which contributed to instability.

We are not convinced that the household debt mechanism is the correct one. Two underlying issues give us pause. First, research by Mason & Jayadev (2014) strongly suggests that "Fisher

[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).

dynamics," their terminology for interest rate changes, inflation, and income growth, account for most, if not all, of the increase in US household leverage since 1980. Leverage grew not because of individual household choices or institutional policy shifts (with the exception of interest rates) but due to broader macroeconomic dynamics. Second, debt may disguise the true structural forces driving economic stability. In a summary of the inequality-crisis literature, Jayadev (2013) concludes, "wealth/net worth may be the more critical variable, especially when financial crises are driven by asset bubbles." (Indeed, Morelli & Atkinson (2015) survey 84 crises across 21 countries over the past century, examining both the levels of and changes in income inequality preceding a crisis episode, and conclude that the impact of either on financial crises is ambiguous.) Because one party's liability is another's asset, we turn our empirical focus to the latter half of the balance sheet. That is, we focus on wealth inequality as a determinant of financial crises.

Presenting empirical evidence of the relationship between wealth inequality, aggregate wealth, and financial crises, this paper argues that wealth inequality, in an economy with high levels of aggregate wealth, has a positive, robust, and meaningful marginal effect on the likelihood of a financial crisis, particularly a stock market crash—or a concurrent stock market crash and banking crisis. We rely on a panel data set of nine Western European and Anglo-Saxon countries over the past century, regressing a set of reduced-formed, two-way fixed effects linear probability models. Our results hold when controlling for financial sector development, private sector credit, top marginal tax rates, average rates of return, and GDP growth. Furthermore, no significant relationships are found when income inequality replaces wealth inequality in our model. This supports our contention that wealth inequality captures certain structural attributes of the economy that income inequality cannot. And some structural arrangements are more stable than others.

Why should the distribution of stocks (assets) be a more relevant factor in instability than the distribution of flows (income)? We argue that asset accumulations serve as a proxy for the underlying structural relationships of an economic network. Axel Leijonhufvud described an economy as a "web of contracts and understandings" between agents. In such an economic web, financial assets and liabilities link parties. They connect households and individuals who are codependent on the future cash flows such assets represent. The total number of links or connections represents an individual's *degree* and the distribution of those assets can be described through a *degree distri-*

bution, a useful summary statistic in graph theory that characterizes large networks. Much like the financial network contagion literature (see Allen & Gale (2000), Battiston et al. (2012), and Elliott et al. (2014), among others) we argue that the topology of the network—as chiefly determined by the degree distribution—characterizes its level of stability.

We show in Hauner (2016), using a simple network model of interpersonal wealth distribution, that inequality can directly contribute to the stability of the network structure in the event of a shock. Stability is defined as the number of individuals in the network economy whose net worth drops below some threshold. When assets are distributed evenly, a single shock to one individual's wealth is quickly absorbed by connected individuals who all have similar financial wealth. But when assets are unequally distributed, a shock is less likely to be absorbed. Contagion spreads as failure costs wipe out collateral wealth—the underlying value of all network assets. Across model simulations, network contagion is jointly determined by (1) the level of wealth inequality, and (2) total wealth.

The remainder of the paper is organized as follows: in Section 2 we outline our reduced-form econometric model, focussing on marginal effects we expect to find; Section 3 presents our data and Section 4 our estimation results; in Section 5 we share robustness checks, bolstering our initial findings, and Section 6 concludes.

2 Methodology

In this section we derive a reduced-form empirical model based on insights from the theoretical framework in Hauner (2016) as well as the broader financial contagion literature. From the former we incorporate the finding, demonstrated in simulations, that aggregate wealth and its distribution jointly determine the stability of a financial network. That is, wealth inequality only positively impacts the instability of sufficiently rich economies. Total national wealth, individually, has a nonlinear effect on economic network stability, as argued by Gai & Kapadia (2010) and Elliott et al. (2014), initially leading to more instability but then becoming more stabilizing.

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 W/Y. These explanatory variables are interacted to capture their jointly deterministic role in network instability. Our linear probability model thus takes the following form, including country and year fixed effects:

$$crisis_{it}^{k} = \delta_i + \delta_t + \beta_1 top1nw_{it-2} + \beta_2 \left(\frac{W}{Y}\right)_{it-2} + \beta_3 top1nw \times \left(\frac{W}{Y}\right)_{it-2} + \gamma' \mathbf{X}_{it-2} + \varepsilon_{it}. \quad (1)$$

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 W/Y is the aggregate wealth-income ratio for a given country. The vector $\mathbf{X}$ contains a set of control variables including financial sector size, estimated averages rates of return on capital, and average GDP per capita growth rates. Lag-length, included to clarify the direction of the proposed relationship, was selected by information criteria.[2]

In order to test the nonlinear relationship between aggregate wealth and instability suggested in the literature (and echoed by the simulations in Hauner (2016)) we add a quadratic specification for aggregate wealth.

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

Of course the linear probability model (LPM) is not an applied researcher's first choice to estimate a binary dependent variable regression equation. Aside from predicted probabilities that land outside the unit interval (and often below zero), the LPM implies $\mathbb{E}[\varepsilon] = 0$ and therefore that the estimated coefficient must equal the true parameter value. We cautiously proceed with the LPM, however, because we emphasize the positive or negative marginal effects of wealth inequality and aggregate wealth. These can interact nonlinearly, making any interpretation of marginal effects in a logit model difficult. There also exist significant gaps in our time series data, leading to irregularly-

[2]The income inequality-crisis literature has used both contemporaneous and lagged specifications with mixed results.

spaced observations that may or may not be clustered around a crisis episode (see Figure 3). Thus it becomes important to control for both time and country fixed effects as allowed by the LPM.

We also use the LPM specification because our model is not primarily intended as a predictive tool but rather as an analytical measure of historical significance—though as a robustness exercise we do present country-specific prediction results of the fixed effect logit model in Section 5.3. Country and year fixed effects also help account for the endogeneity any macroeconomic system entails and between-country crisis correlations—an imperfect remedy. Other measures such as averaging observations across half-decade intervals, or redefining a binary outcome, are also taken.

As a robustness check, in Section 5, we estimate fixed effect logit models for many of the same relationships, but are only able to control for country fixed effects. A two-way fixed effects logit estimator, as elegantly laid out by Charbonneau (2014), is not yet feasible for applied work. Any significant results merely support the financial network framework for relating macroeconomic stability to wealth distributions.

2.1 Marginal Effects

The marginal effects of wealth inequality $top1nw$ and aggregate wealth W/Y on the likelihood of a financial crisis imply, from Equation (1), that

$$\frac{\partial crisis_{it}^{k}}{\partial top1nw_{it-2}} = \beta_1 + \beta_3 \left(\frac{W}{Y}\right)_{it-2} \lesseqqgtr 0 \tag{3}$$

and

$$\frac{\partial crisis_{it}^{k}}{\partial (\frac{W}{Y})_{it-2}} = \beta_2 + \beta_3 top1nw_{it-2} \lesseqqgtr 0. \tag{4}$$

Coefficients β_1 and β_2 are now difficult to interpret. For example, if β_1 is to be economically significant then W/Y must equal zero, an impossible outcome. An analogous scenario afflicts β_2. 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 null hypothesis $\mathcal{H}_1 : \beta_3 = 0$, in favor of a positive alternative where $\beta_3 > 0$, then wealth inequality and aggregate wealth may both contribute to financial instability.

From Equation (2) we consider the nonmonotonic effects of aggregate wealth on instability. The marginal effect becomes

$$\frac{\partial crisis_{it}^{k}}{\partial(\frac{W}{Y})_{it-2}} = \beta_2 + 2\beta_4 \left(\frac{W}{Y}\right)_{it-2} + \beta_3 top1nw_{it-2} \lesseqgtr 0. \tag{5}$$

Rejecting the 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-shaped relationship with instability, first increasing but then decreasing.

3 Data

Wealth Inequality

The net worth held by the top 1% of households is our measure of wealth inequality.[3] A survey by Roine & Waldenström (2015) collects ten national time series of wealth concentration.[4] Data for Italy (Brandolini et al. (2006)) and Spain (Alvaredo & Saez (2009)) are also included. Each country's time series is dependent on sampling methods and weighting, tax evasion, mortality rate calculations, and the basic unit of measurement. Despite heterogeneous methodology, but also given the lack of a consistent historical survey across countries, we employ the data aware of these shortcomings.[5] 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 1 below). There is, however, 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 1b.) 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.

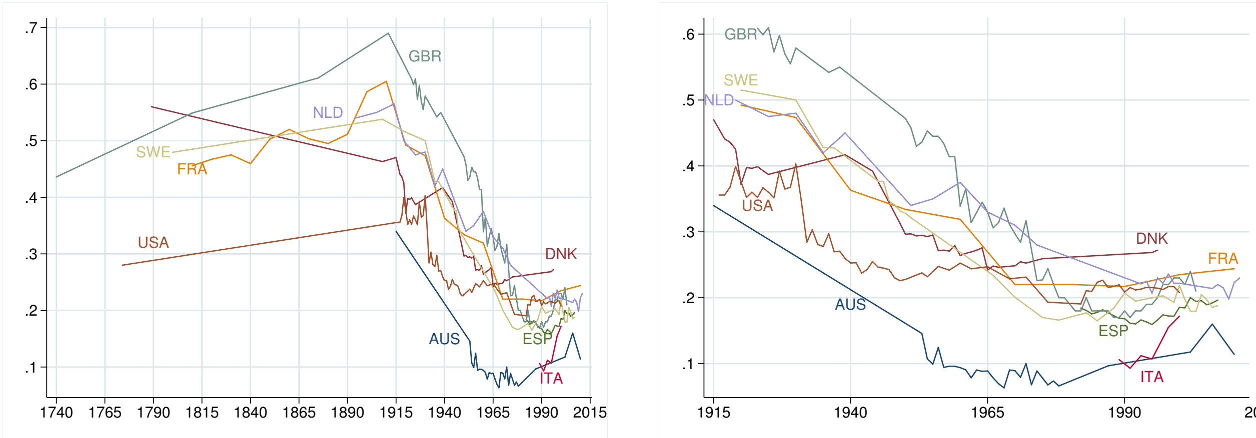
Aggregate Wealth

Piketty & Zucman (2014) estimate a country's national wealth, calling it the capital-income

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

[4] 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)

[5] Roine & Waldenström (2015) also cite studies comparing household versus individual surveys which find "no important differences."



(a) 1740–2012 **(b)** 1915–2012

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

ratio, by summing all marketable capital assets at their current price levels.[6] We call this the aggregate wealth-income ratio. Assets include productive capital such as land and factories, financial capital like pensions and life insurance, and also capital assets like art, but exclude durable goods, an important source of wealth and collateral for low-income households, claims on future government spending and transfers, and human capital—a key determinant of contemporary incomes.

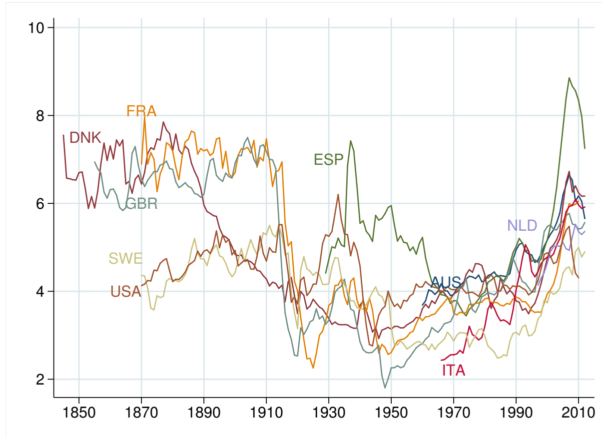
The Piketty & Zucman (2014) data cover a panel of seven countries from 1845 through 2012.[7] It is supplemented with national wealth data estimates for Sweden (from Waldenström (2015)) and Denmark (from Abildgren (2015)).[8] Both series adhere to the methodological approach of Piketty & Zucman (2014). Some general trends emerge (see Figure 2): all countries increase aggregate wealth over the last 40 years, with some beginning around 60 years ago; all countries, except Sweden and the US, had very 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

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

[7] 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.

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



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

Figure 2: Aggregate Wealth-Income Ratios

the US. Depending on model specification and estimation method, our panel contains up to 273 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, established through 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.[9] 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 3. We do not consider existing continuous measures of financial stress because they only begin in the 1990s.[10] Tables 1–2 summarize the number of crisis episodes per country.

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

[10] 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

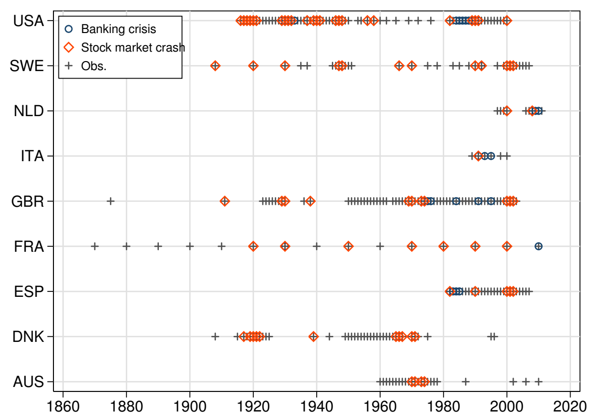
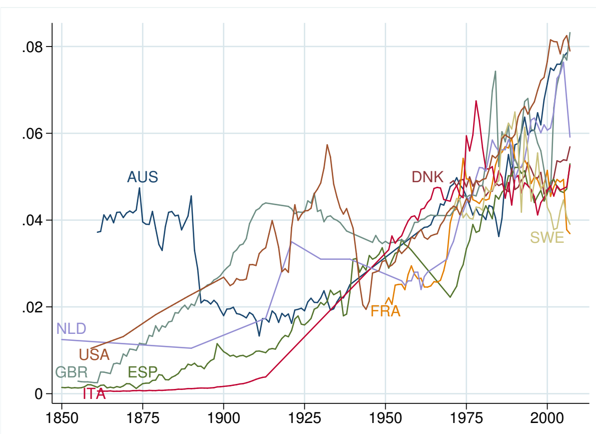


Figure 3: Crises Timeline

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 4).



Source: Philippon & Reshef (2013)

Figure 4: Finance Value Added Share of Income

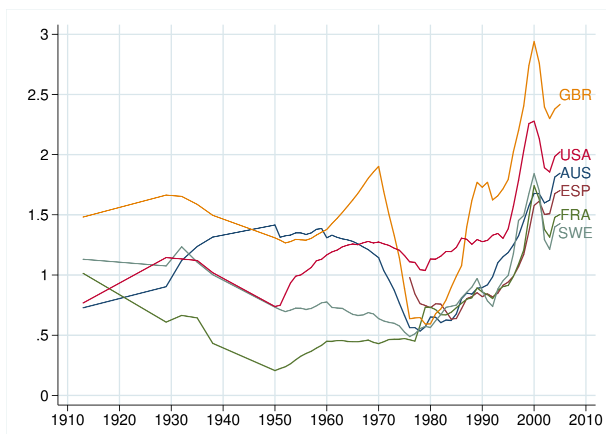


Figure 5: Financial Development (% GDP)

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

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.

return on capital, and private sector credit—both as a share of GDP.[11] Data begin in 1900 and continue through 2006. (See Figures 5–6.) Including total private credit accounts for the most cited determinant of financial crises in the literature.[12] Top marginal tax rates (Figure 7) 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.[13] 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).

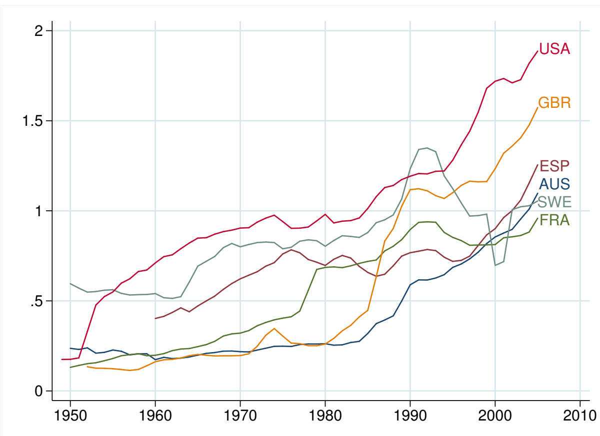


Figure 6: Private Sector Credit (% GDP)

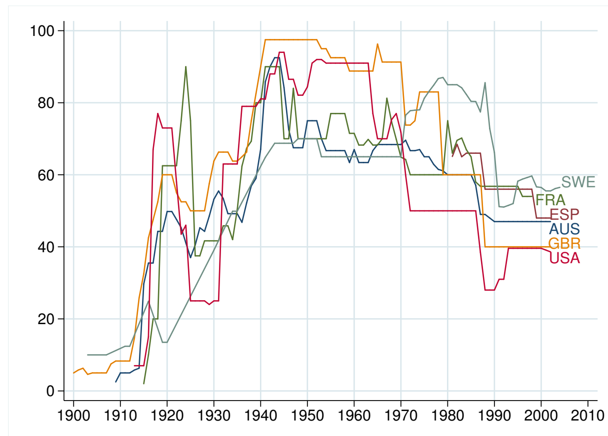


Figure 7: Top Marginal Tax Rates (%)

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 inequality $r > g$ and Fuest et al. (2015) corroborate it empirically. Controlling for both r and g ensures that any apparent effect of wealth inequality on instability is not simply 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 Tables 3–7 for summary statistics across variables and subsamples.)

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

4 Results

We first present OLS results for various specifications of the reduced form linear probability model in equation (1). Of primary concern are the marginal effects of wealth inequality and aggregate wealth on crises (Equations (3)–(4)). 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 8 and the likelihood of stock market crashes in Table 9. 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 largest panel of nine countries.

The interacted term of inequality and wealth is significant (at 5%) in our preferred banking crisis model (Table 8, Column 2), but insignificant in all other specifications. In contrast, the interaction in our stock market crash model (Table 9) 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, perhaps 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 2).

4.1 Marginal Effects

Wealth inequality and aggregate wealth alone have negative but insignificant effects on banking crises (Table 8, Column 2). The marginal effect of aggregate wealth on banking crises is

$$\frac{\partial crisis^b_{it}}{\partial(\frac{W}{Y})_{it-2}} = -0.187 + 1.845 top1nw_{it-2}, \tag{6}$$

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 8a, 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 our horizontal axis variable (wealth inequality in Figure 8) is given by the kernel density plot, where dashed vertical lines indicate the median observation.

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

$$\frac{\partial crisis^s_{it}}{\partial(\frac{W}{Y})_{it-2}} = -0.570 + 2.306 top1nw_{it-2}. \tag{7}$$

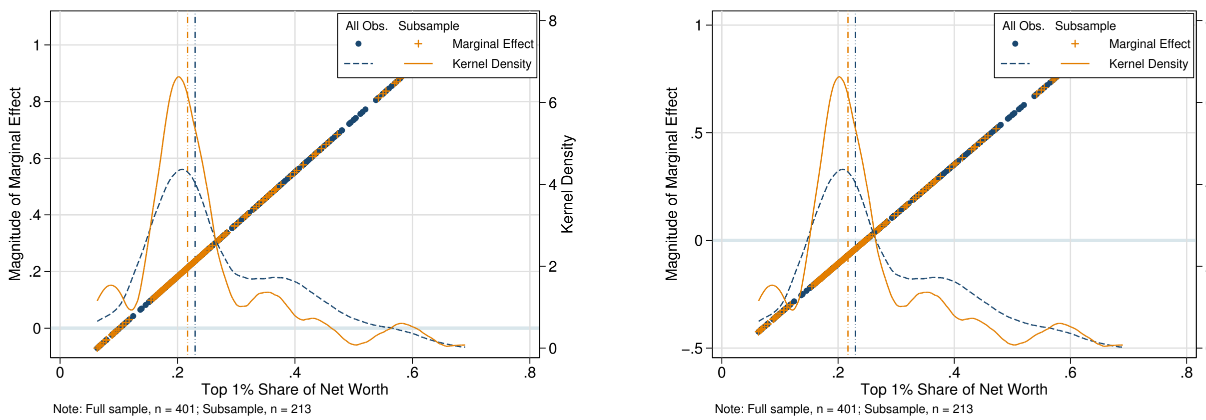
In order for this marginal effect to be positive, top wealth shares must be greater than 0.247 according to the model specification above—past the median values of either sample (see Figure 8b).

Next, we consider the marginal effects of wealth inequality. Concerning banking crises (Table 8, Column 2) we find the following:

$$\frac{\partial crisis^b_{it}}{\partial top1nw_{it-2}} = -2.615 + 1.845 \left(\frac{W}{Y}\right)_{it-2} - 28.309 finsh_{it-2}. \tag{8}$$

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 9a.)

The marginal effect of wealth inequality on stock market crashes, from Table 9, Column 2, is



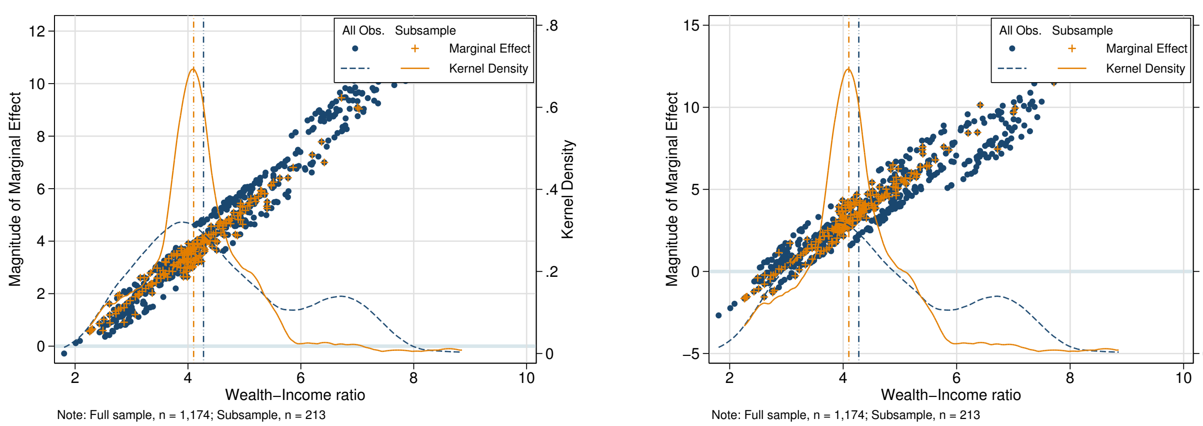
(a) Banking Crises **(b)** Stock Market Crashes

Figure 8: Marginal Effect of Aggregate Wealth on Likelihood of Crisis: LPM

similarly positive and increasing.

$$\frac{\partial crisis_{it}^{s}}{\partial top1nw_{it-2}} = -8.616 + 2.306\left(\frac{W}{Y}\right)_{it-2} + 50.426 finsh_{it-2}. \tag{9}$$

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 9b.)



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

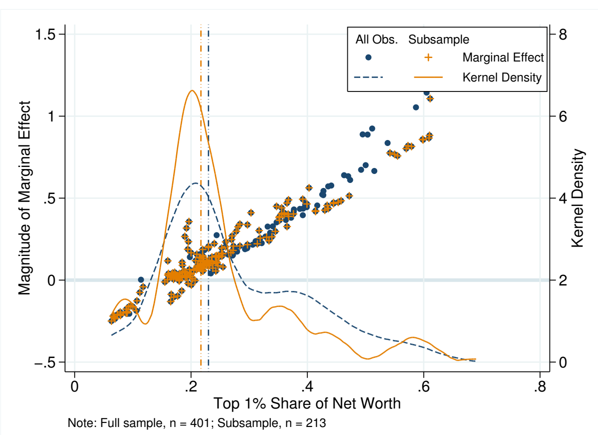
Figure 9: Marginal Effect of Wealth Inequality on Likelihood of Crisis: LPM

Overall, we reject our first null hypothesis ($\mathcal{H}_1 : \beta_3 = 0$) and support the network interpretation of wealth inequality's positive role in financial instability. 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 9 support our model's contention that the marginal effect of wealth inequality on instability is increasing for richer economies. 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 more objective definition and greater prevalence in the data.

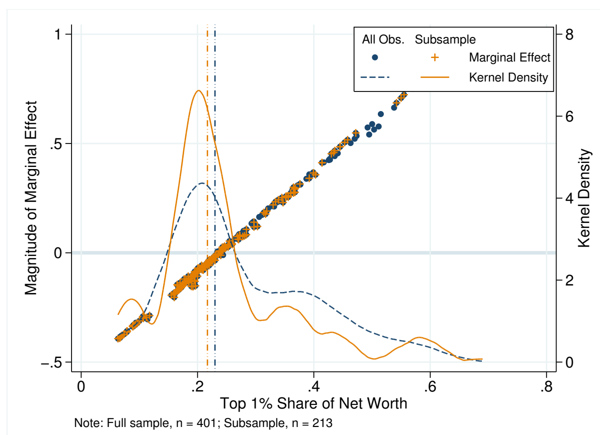
These results support our contention that the distribution of wealth is an important component in determining the likelihood of some future financial crisis in a wealthy economy. A rising maldistribution of wealth implies any negative income shock has the potential to hurt the finances of a larger fraction of the economy.

4.2 Aggregate Wealth and Instability

Our theoretical framework in Hauner (2016) predicted an inverted U-shaped relationship between rising aggregate wealth and instability—echoing nonlinearities described in the financial network contagion literature. That is, as the network became wealthier instability increased but eventually began to decrease. Least squares estimates of Equation (2) are presented in Table 10, all based on the second specification in Tables 8 and 9.



(a) Aggregate Wealth



(b) Wealth Inequality

Figure 10: 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 (5) and Figure 10) 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 8) leave the question unsettled.

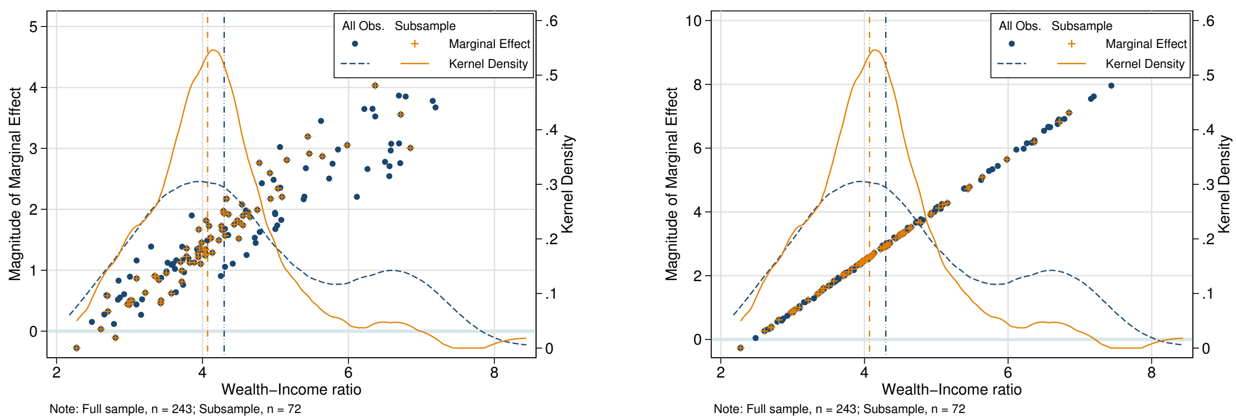
4.3 Additional Crisis Regressors

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.[14] (See the timeline in Figure 3 indicating crisis episodes and data observations in our largest subsample.) Another concern is that crises are correlated across countries.

Considering these possibilities, we examine long-run relationships by averaging all the variables (both independent and dependent) across five-year horizons. The dependent variable now takes a value of 1 if the crisis type occurs over the half-decade interval, and a 0 otherwise. This forces international correlations of crises to be absorbed by the wider time window, and places the wealth inequality-crisis relationship in more of a long-run context.

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 11–12.) A fully specified model is most significant when describing the relationship with banking crises, while more parsimonious models are most significant when describing the relation-

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



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

Figure 11: MARGINAL EFFECT OF WEALTH INEQUALITY ON LIKELIHOOD OF FINANCIAL CRISIS: 5 YEAR AVERAGES

NOTES: Based on model specification (2) in Tables 11 and 12.

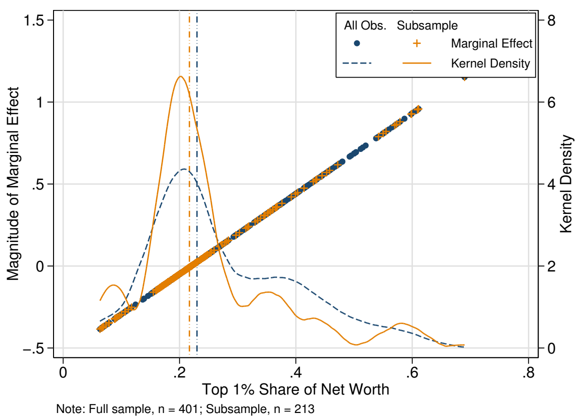
ship with stock market crashes.

For consistent comparisons to previous estimates we focus on the second model specification (Columns 2) when examining marginal effects (Figure 11). Wealth inequality demonstrates a strongly positive and increasing marginal effect on stock market crashes over five-year periods—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.

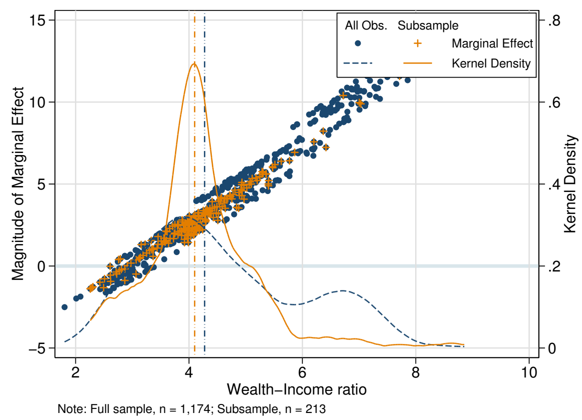
To further test the constancy of the wealth inequality-financial crisis relationship, we redefine our crisis indicator. We define a *large crisis* to be when both types occur within the same year (i.e. the intersection of banking crises and stock market crashes). Regression results (presented in Table 13) 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, when controlling for financial sector size, is positive and increasing. It remains so for wealth-income ratios above the bottom 5^{th} or 10^{th} percentiles—depending on the relative financial sector size.

We repeat the exercise of averaging over five years for our new *large crisis* indicator. Estimation results are shown in Table 14 and are very significant in the first two specifications, and of comparable magnitude and sign (though insignificant) in the fully specified models (Columns 3–4). The overwhelming majority of observations yield a meaningful, positive, and increasing marginal effect of wealth inequality on the likelihood of both a banking crisis and stock market crash occurring within the same year for a given country.



(a) Aggregate Wealth



(b) Wealth Inequality

Figure 12: Marginal Effects on Likelihood of Both Crises

Notes: Based on model specification (2) in Table 13.

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 underpin our contention that the distribution of accumulated assets imparts structural information about the economy which has implications for its future financial stability.

5 Robustness Checks

We present findings on and discuss three robustness checks of our empirical results: First, the empirical relationship in Equation (1) is estimated as a fixed effects logit model; Second, we substitute

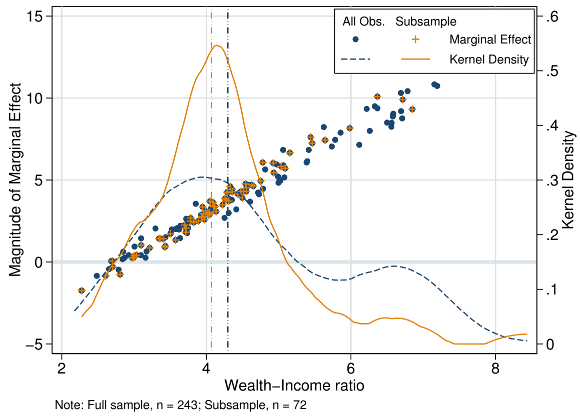


Figure 13: Marginal Effect of Wealth Inequality on Likelihood of Both Crises: 5 Year Averages

Notes: Based on model specification (2) in Table 14.

income for wealth as our inequality measure to test if stocks do in fact have more explanatory power than flows; Lastly, we compare the predicted probabilities of our logit models on a country-by-country basis with actual crisis episodes.

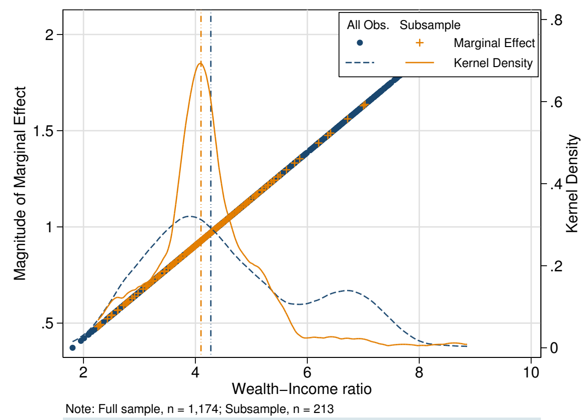
5.1 Fixed Effect Logit

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:

$$\Pr(crisis_{it}^{k}=1)=\Lambda\left[\delta_i+\beta_1 top1nw_{it-2}+\beta_2\left(\frac{W}{Y}\right)_{it-2}+\beta_3 top1nw\times\left(\frac{W}{Y}\right)_{it-2}+\gamma'\mathbf{X}_{it-3}\right] \quad (10)$$

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 15–16. 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. (Furthermore, the fully specified models, when estimated against the half-decade averaged data, often perfectly determine the outcome.) Estimating the marginal effects of wealth inequality on both crisis types yields the plots in Figure 14.



(b) Stock Market Crashes

(a) Banking Crises

Figure 14: Marginal Effect of Wealth Inequality on Likelihood of Crisis: Logit Model

We find negative but increasing marginal effects of inequality on banking crises, the discretionarily coded crisis outcome, but consistently positive, and increasing, marginal effects on the likelihood of stock market crashes. Additional fixed effect logit results on *large* crises (Table 17), do find positive estimates of the interacted term across specifications (though insignificant) and yield strictly positive and increasing marginal effects of wealth inequality.

While our preferred parsimonious logit model (Column 2) is insignificant, it is of similar sign and magnitude as our LPM results. The fixed effect logit results alone are insufficient to falsify the existence of a positive relationship between wealth inequality and financial instability in rich economies. The lack of a year fixed effect and the irregularity of the observations pose additional hurdles to any strong inference from the fixed effect logit results.

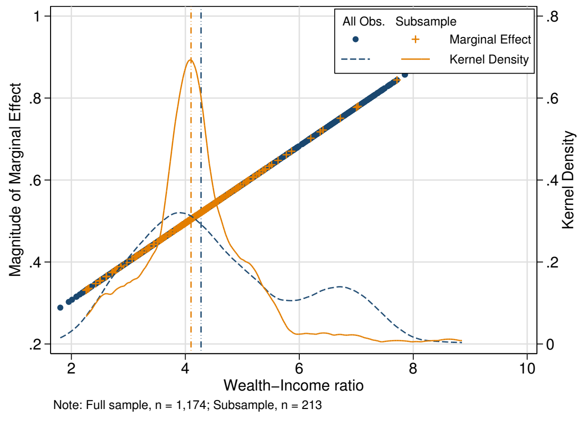


Figure 15: Marginal Effect of Wealth Inequality on Likelihood of *Both* Crises: Logit Model

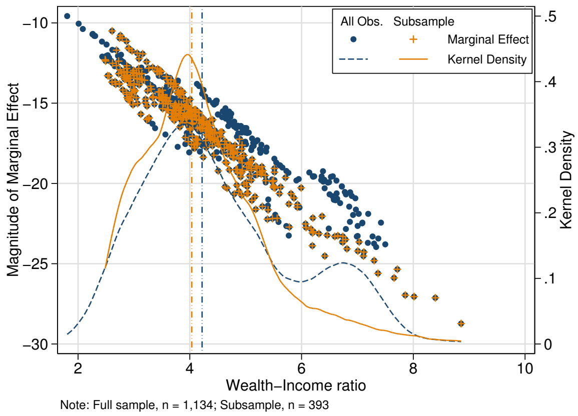
5.2 Income Inequality

Is our emphasis on wealth inequality rather than income inequality warranted? Or, does income inequality also predict skewed cashflow network structures that are similarly unstable? We estimate the same reduced form linear probability model with two-way fixed effects in Equation (1) 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.

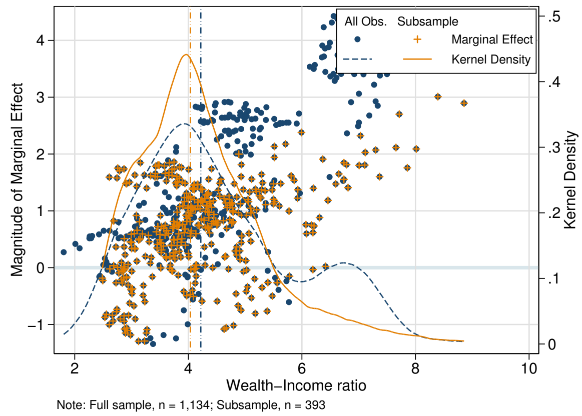
Estimation results are presented in Tables 18 and 19. The impact of income inequality on financial instability is ambiguous and insignificant. Parameter estimates on income inequality and income inequality interacted with the aggregate wealth-income ratio demonstrate a large variance in both sign and magnitude when predicting both crisis types.[15]

Though insignificant, we again analyze the marginal effects of income inequality as a comparison to Figures 8 and 9 above. Marginal effects results are shown in Figure 16. The effect (based on specification 2, to mirror the wealth models) is starkly negative and decreasing for banking crises, across all wealth-income ratios, suggesting a decreasing impact from inequality on banking crises, the opposite of our model's predictions and our empirical findings for wealth inequality. The marginal effect of inequality on stock market crashes is mixed, but generally more positive and increasing than the banking crisis case. This is true both in the full sample of wealth-income ratios and the specification's subsample.

[15] 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.



(a) Banking Crises



(b) Stock Market Crashes

Figure 16: Marginal Effect of Income Inequality on Likelihood of Financial Crisis

A Davidson & MacKinnon (1981) J-test of model specification confirms the lack of explanatory power for income inequality in our model.[16] These results further support our claim, and statistical evidence, that the unequal distribution of financial assets (a stock) rather than incomes (a flow) positively influences a wealthy economy's likelihood of crisis.

5.3 Predictions

While we underscore past significance of marginal effects, the relationship between aggregate wealth and its distribution should correspond to actual financial crisis episodes. That is, our models' within-sample predicted probabilities should correspond to actual crises for a given country. To generate these forecasts we utilize the logit model so that predicted values, constrained to the unit interval, have clear interpretations. Estimating equations country-by-country eliminates needed country fixed effects. (Including year fixed effects only yields perfectly determined outcomes.)

The limitations of our aggregate wealth and wealth inequality data imply that we can only estimate predictions for four countries: the United States, United Kingdom, Denmark, and Sweden. The United States wealth inequality data, in order to extend the time series from 2000 through 2012, now come from Saez & Zucman (2014) who use the capitalization estimation method rather

[16]Though 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.

than Kopczuk & Saez (2004) who use the estate tax method.

We test three model specifications whenever possible.

Lag only:

$$\Pr(crisis_{it}^{k}=1)=\Lambda\left[\alpha+\beta top1nw\times\left(\frac{W}{Y}\right)_{it-2}+\varepsilon_{it}\right] \tag{11}$$

Model 1:

$$\Pr(crisis_{it}^{k}=1)=\Lambda\left[\alpha+\beta_1 top1nw_{it-2}+\beta_2\left(\frac{W}{Y}\right)_{it-2}+\beta_3 top1nw\times\left(\frac{W}{Y}\right)_{it-2}+\varepsilon_{it}\right] \tag{12}$$

Model 2:

$$\Pr(crisis_{it}^{k}=1)=\Lambda\left[\alpha+\beta_1 top1nw_{it-2}+\beta_2\left(\frac{W}{Y}\right)_{it-2}+\beta_3 top1nw\times\left(\frac{W}{Y}\right)_{it-2}+\beta_4 finsh_{it-2}+\varepsilon_{it}\right] \tag{13}$$

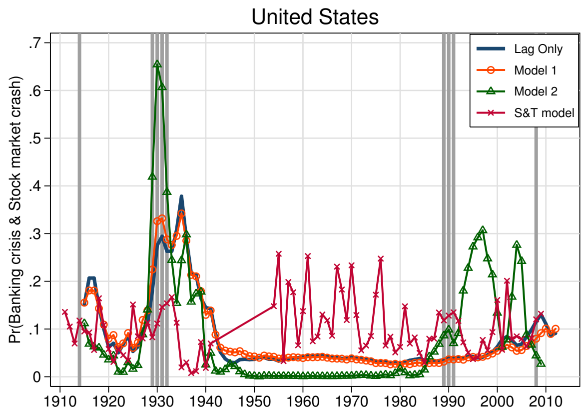
Each of the above models are compared against the lagged real-changes-in-credit model of Schularick & Taylor (2012), henceforth S&T:

$$\Pr(crisis_{it}^{k}=1)=\Lambda\left[\alpha+\sum_{k=1}^{5}\beta_k\Delta\ln rcredit_{it-k}+\varepsilon_{it}\right]. \tag{14}$$

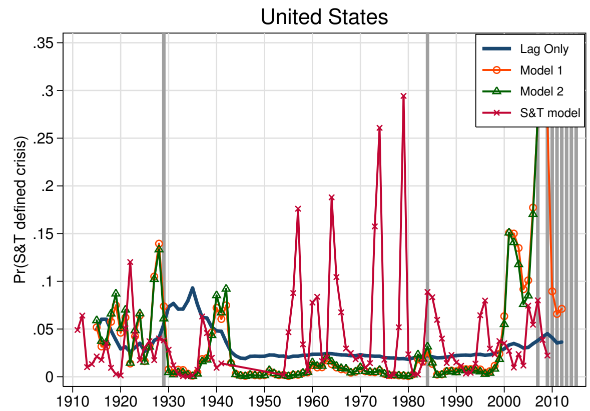
Two crisis indicator variables are compared. The first is our *large crisis* indicator, wherein both a banking crisis and stock market crash occur within the same year in a given country. This double financial trauma best encapsulates the intuitive notion of a financial crisis. The second indicator is a binary financial crisis variable from S&T, which omits some large crises but also includes additional ones and thus differs from the Reinhart & Rogoff dates.

Results are presented graphically in the figures below, with individual predicted probabilities plotted to illustrate the relative sparsity of some country-level data. Vertical grey bars represent a crisis year. In the case of Sweden, model 2 (Equation (13)) is not estimated since financial sector share values greater than 0.062 predict the outcome perfectly. And in the case of Denmark, no crises occur for the subsample of observations for which financial sector share data are available.

Our models collectively perform best in the case of the United States (Figure 17). For both



(a) Large Crises



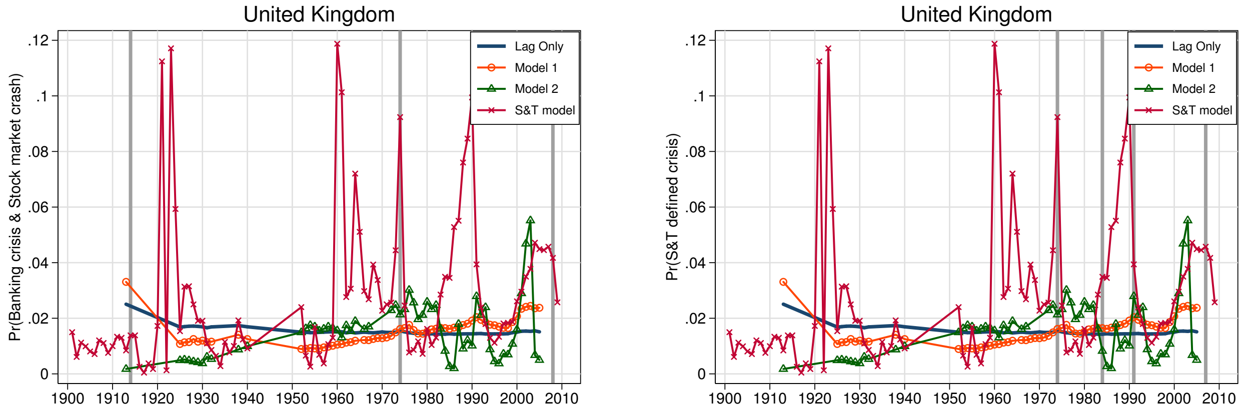
(b) S&T Crises

Figure 17: United States

crisis indicators, our models peak during the Great Crash, recede during the postwar period, and then slowly increase beginning in the 1980s with spikes in the late 1980s/early 1990s. Equation (13) (Model 2) is particularly nuanced in tracing economic instability concerning large crises, jumping in late 1990s, to reflect the dot-com bubble, itself not categorized as a large crisis, and again near 2006, to presage the eventual subprime mortgage crisis. Both equations (12) and (13) (Models 1 and 2) perform equally well to predict instability as defined by S&T crises, climbing calamitously before both the Great Crash and the more recent global financial crisis. The univariate lag only model (Equation (11)) performs best in determining large crises only. Our models are each better predictors than the S&T model, which is too volatile. Its relative changes in probability reflect business cycles more than any genuine financial stability risk. One simple reason for the success of our models is that there exist a large number of observations (98 and 95) from which to estimate.

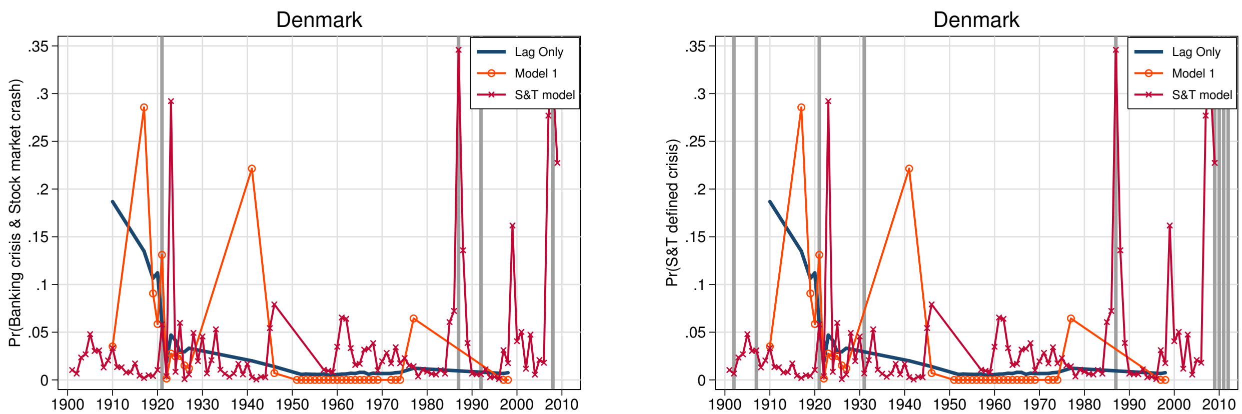
The United Kingdom case also lends credibility to Models 1 and 2 (Figure 18), despite having only 60 or 64 observations from which to estimate. Both models (Equations (12) and (13)) increase predicted probability, with a relative peak, near the 1973 oil embargo crisis. They also increase before the S&T defined crisis of 1991 and then increase again in anticipation of the global financial crisis in 2007. The S&T model again exhibits tremendous volatility, crying wolf during eras of comparative financial market tranquility.

The Danish and Swedish predictions (Figures 19–20) perform poorly given the irregular and infrequent data—only 38 and 31 observations, respectively. The peaks at the beginning of the



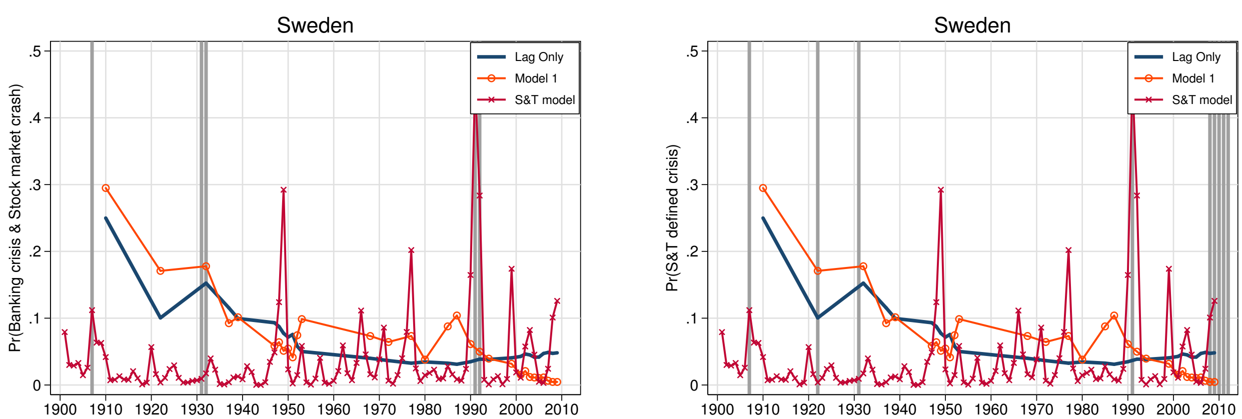
(a) Large Crises **(b)** S&T Crises

Figure 18: United Kingdom



(a) Large Crises **(b)** S&T Crises

Figure 19: Denmark



(a) Large Crises **(b)** S&T Crises

Figure 20: Sweden

predicted series appear to correspond to crises, however, our models completely miss on the recent global financial crisis, lacking any foresight. The Swedish predictions (Model 1) do correlate with the real estate crisis in the early 1990s, however the relative increase in probability is recent and obfuscated by the similar probabilities estimated throughout the late 1950s and 1960s. Given more observations in real credit data, the S&T model performs relatively well, with the highest peaks in probability generally corresponding to actual crisis episodes, except for some conspicuous misses.

Overall, our empirical results are consistent enough to lend support to our hypothesis that wealth inequality, in sufficiently wealthy economies, plays a unique role in macroeconomic stability, one that income inequality does not, and cannot, capture. However, more data are needed to help defend this conclusion beyond the Anglo-Saxon paradigm.

6 Conclusion

Keynes once described the relationship between debtors and creditors as forming "the ultimate foundation of capitalism." The economic theory pinning down our empirical approach is a radically simplified interpretation of a financial economy, one that reverts to this "ultimate foundation" by eliminating intermediaries and instead relies on the latent financial pathways that link individual asset and liability holders.[17] The distribution of wealth therefore acts as a sufficient statistic to describe the arrangement of linkages in our networked financial economy. The aggregate wealth describes the total number of links. Together, the total wealth and its distribution are key determinants of the network economy's robustness in the event of a shock. More unequal distributions in rich economies create a structure of interconnectedness that is more likely to result in a financial crisis if shocked. This theory echoes much of the intuition from the banking network contagion literature.

This paper tests this theory empirically with a reduced-form linear probability model including two-way fixed effects on panel data from nine countries (Australia, Denmark, France, Italy, the Netherlands, Spain, Sweden, the UK, and the US) with historic data beginning in 1870. The

[17] See Hauner (2016).

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. The predictive performance of our logit models, particularly the US and UK cases, gives further support. 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).

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. Rising inequality will always have wide welfare effects, but macroeconomic health may also be at stake.

A number of statistical limitations, however, motivate further investigation. First and foremost is the overall paucity of wealth inequality data. While annual top wealth shares estimates exist for the United States under numerous methodologies,[18] comparably robust, annual data are lacking for most other developed economies let alone developing ones. Second, is the potential estimation bias from crises correlated between countries. And third is the inability to harness a two-way fixed effect logistic model for applied work.

We conclude by quoting Morelli & Atkinson (2015): "the inequality-crisis nexus can apply independently to specific cases or country and that, if existent, it might not be an iron law." It may be that global inequality, given the interconnectedness of all financial markets, may be the most relevant for contemporary financial crises.

[18] See Kopczuk (2015) for a summary.

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Tables

Table 1: 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 2: 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 3: 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 4: 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 5: 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 6: 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 7: 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 3.

Table 8: 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 × 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 × 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 9: 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 × 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 × 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 10: 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.

Table 11: 5 Year Averages: Likelihood of Banking Crisis

	(1)	(2)	(3)	(4)
Top 1% Shr Net Worth	-5.059	-6.353	-4.596	-17.701*
	(4.117)	(4.507)	(4.816)	(6.939)
Wealth-Income ratio	-0.160	-0.134	-0.274	-1.771
	(0.407)	(0.423)	(0.587)	(1.257)
Top 1% Shr Net Worth × Wealth-Income ratio	1.579	1.483	2.144	8.208*
	(1.287)	(1.338)	(2.492)	(3.877)
Finance Shr of Income	-10.851	-17.086*	-19.777*	1.789
	(6.216)	(8.314)	(10.446)	(26.043)
Top 1% Shr Net Worth × Finance Shr of Income		39.741	3.859	-51.546
		(57.156)	(102.115)	(172.233)
$\tilde{r}$			7.548**	8.321
			(2.853)	(4.788)
$\hat{g}$			-13.124	4.347
			(9.258)	(7.852)
Private Sector Credit				-0.015
				(0.390)
Top Marginal Tax Rate				-0.012
				(0.007)
AIC	45.5	45.3	34.1	13.3
R^2	0.520	0.521	0.559	0.670
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 five year intervals. Dependent variable is 1 if crisis type occurs in given country over five years. Linear probability model is estimated with two-way fixed effects (2FE), controlling for country and half-decade. 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 12: 5 Year Averages: Likelihood of Stock Market Crash

	(1)	(2)	(3)	(4)
Top 1% Shr Net Worth	-5.488	-3.953	-5.912	-3.477
	(3.700)	(5.330)	(4.755)	(5.367)
Wealth-Income ratio	-0.668*	-0.699*	-0.964**	0.028
	(0.340)	(0.362)	(0.322)	(0.539)
Top 1% Shr Net Worth × Wealth-Income ratio	2.403*	2.517*	3.750**	1.507
	(1.214)	(1.317)	(1.396)	(2.457)
Finance Shr of Income	-5.360	2.036	7.962	-6.931
	(4.077)	(18.994)	(14.680)	(24.550)
Top 1% Shr Net Worth × Finance Shr of Income		-47.140	-71.228	66.456
		(128.467)	(108.026)	(135.169)
$\tilde{r}$			-4.185	-8.228
			(3.033)	(6.276)
$\hat{g}$			5.168	-22.780**
			(4.052)	(6.213)
Private Sector Credit				-0.597
				(0.601)
Top Marginal Tax Rate				-0.025**
				(0.009)
AIC	29.4	29.0	29.8	10.4
R^2	0.643	0.645	0.624	0.687
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 five year intervals. Dependent variable is 1 if crisis type occurs in given country over five years. Linear probability model is estimated with two-way fixed effects (2FE), controlling for country and half-decade. 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 13: 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 × 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 × 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: All variables are averaged over five year intervals. Dependent variable is 1 if crisis type occurs in given country over five years. Linear probability model is estimated with two-way fixed effects (2FE), controlling for country and half-decade. 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 14: 5 Year Averages: Likelihood of *Both* Banking Crisis and Stock Market Crash

	(1)	(2)	(3)	(4)
Top 1% Shr Net Worth	-7.662*	-8.675*	-7.176	-13.649**
	(3.480)	(3.886)	(3.989)	(3.605)
Wealth-Income ratio	-0.635	-0.614	-0.695	-1.369*
	(0.344)	(0.356)	(0.518)	(0.607)
Top 1% Shr Net Worth × Wealth-Income ratio	2.642*	2.567*	2.868	6.399***
	(1.163)	(1.188)	(2.029)	(1.218)
Finance Shr of Income	-2.249	-7.126	-11.155	9.411
	(3.870)	(9.097)	(13.365)	(24.286)
Top 1% Shr Net Worth × Finance Shr of Income		31.092	29.968	-4.189
		(48.477)	(90.193)	(116.751)
$\tilde{r}$			1.263	-2.183
			(3.416)	(4.032)
$\hat{g}$			-3.708	-2.280
			(7.613)	(8.797)
Private Sector Credit				-0.252
				(0.425)
Top Marginal Tax Rate				-0.010**
				(0.004)
AIC	16.2	16.0	14.6	-4.4
R^2	0.521	0.523	0.481	0.618
Countries	9	9	9	6
Obs	72	72	59	45

Standard errors in parentheses

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

Notes: All variables are averaged over five year intervals. Dependent variable is 1 if both crisis types occur in given country over five years. Linear probability model is estimated with two-way fixed effects (2FE), controlling for country and half-decade. 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 15: 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 $\times$ 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 16: 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.

Table 17: FIXED EFFECT LOGIT: LIKELIHOOD OF *Both*

	(1)	(2)	(3)	(4)
Top 1% Shr Net Worth $_{t-2}$	0.992	-3.983	-30.835	-74.147
	(9.739)	(11.577)	(34.958)	(61.249)
Wealth-Income ratio $_{t-2}$	-0.169	-1.886	-3.984	-9.143*
	(1.086)	(1.430)	(2.851)	(5.447)
Top 1% Shr Net Worth × Wealth-Income ratio $_{t-2}$	1.017	3.319	8.063	26.918
	(2.131)	(2.522)	(9.677)	(18.028)
Finance Shr of Income $_{t-2}$		63.617**	56.206	58.455
		(26.381)	(47.604)	(101.804)
$\tilde{r}$ $_{t-2}$			-5.779	-4.658
			(6.003)	(5.823)
$\hat{g}$ $_{t-2}$			15.820	7.537
			(28.070)	(31.762)
Private Sector Credit $_{t-2}$				-6.125
				(4.477)
Top Marginal Tax Rate $_{t-2}$				-0.181**
				(0.085)
AIC	92.3	69.9	43.2	36.9
Pseudo-R^2	0.071	0.143	0.158	0.367
Countries	7	5	4	3
Obs	262	186	123	112

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 both a stock market crash and a banking crisis occur in 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 18: 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 19: 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 $\times$ 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 $\times$ 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.