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, evidence is presented suggesting a unique capacity for the accumulation of assets to increase 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. It is argued that such 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, and hence more unequal countries in wealth face greater financial instability. An economic network hypothesis is proposed for interpreting these results.

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

1 Introduction

Familiar plots from Thomas Piketty and Emmanuel Saez reveal 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. (For example, see Piketty & Saez (2003), Alvaredo et al. (2013), and Piketty & Saez (2014).) This correlation has generated a host of discussions and research into the relationship between income inequality and financial crisis. (See Milanovic (2009), Krugman (2010), and Acemoglu (2011), 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. Lucchino & Morelli (2012) provide an initial summary of the existing theories, highlighting which parts of the income distribution each emphasizes.

The household debt mechanism is not entirely convincing, however. Two underlying issues give pause. First, research by Mason & Jayadev (2014) strongly suggests that "Fisher dynamics," their terminology for interest rate changes, inflation, and income growth, account for most, if not all, of the increases 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 individual's liability is another's asset, the empirical focus turns to the latter half of the balance sheet. It is argued that wealth inequality, rather than income inequality, is the more influential 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, significant, and robust marginal effect on the likelihood of a financial crisis, particularly a stock market crash—or a concurrent stock market crash and banking crisis. Relying on an unbalanced panel data set of nine Western European and Anglo-Saxon countries over the past century, results are drawn from a set of reduced-formed, two-way fixed effects linear probability models. The results hold when accounting for financial sector development, private sector credit, top marginal tax rates, average rates of return on capital, and GDP growth. Furthermore, no significant relationships are found when income inequality replaces wealth inequality in the model. This is evidence of the belief 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 assets (a stock) be a more relevant factor in financial instability than the distribution of income (a flow)? 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. In a network model, the total number of assets or connections represents an individual's *degree* and the distribution of those assets can be described through a *degree distribution*—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) it is argued that the topology of the network—as chiefly determined by the degree distribution—characterizes its level of stability, or the severity of contagion in the event of a shock.

In Hauner (2016), using a simple static network model of interpersonal wealth, it is shown that wealth 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 by the network. Instead, contagion spreads as failure costs, previously absorbed in a more equal network, wipe out collateral wealth—the underlying value of all network assets—from one connected individual to the next. 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: Section 2 outlines the reduced-form econometric model and the marginal effects; Section 3 presents the data and Section 4 the estimation results; in Section 5 some robustness checks are shared, bolstering the initial findings, and Section 6 concludes.

2 Methodology

A reduced-form empirical model is derived in this section based on insights from the theoretical framework in Hauner (2016) as well as the broader financial contagion literature. From the former the finding, demonstrated in simulations, that aggregate wealth and its distribution jointly determine the stability of a financial network in incorporated. That is, wealth inequality only positively contributes to instability in 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. The 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, is selected by information criteria.[1]

In order to test the nonlinear relationship between aggregate wealth and instability suggested in the literature (and echoed by the simulations in Hauner (2016)) a quadratic term for aggregate wealth is added to the model.

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

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

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

that the estimated coefficient must equal the true parameter value. It is cautiously used, however, because emphasis is placed on the positive or negative marginal effects of wealth inequality on the likelihood of a financial crisis. Also, because of the interaction term these effects behave nonlinearly, making any clear interpretation of marginal effects in a logit model difficult. There also exist significant gaps in the time series data, leading to irregularly-spaced observations that may or may not be clustered around a crisis episode (see Figure A.1 in the online supplementary materials). Thus it becomes important to control for both time and country fixed effects as allowed by the LPM. Country and year fixed effects also help account for 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.

Because the model is not primarily intended as a predictive tool to forecast by what percent the probability of crisis changes based on changing wealth distributions, but rather as an analytical measure of historical significance. Any significant results merely prop up the financial network framework for relating macroeconomic stability to wealth distributions. Still, as a robustness exercise, country-specific predicted probabilities from a logit model are shared in Section 5. As another robustness check, fixed effect logit models are estimated for many of the same relationships, though they can only 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.

2.1 Marginal Effects

The marginal effects of wealth inequality $top1nw$ on the likelihood of a financial crisis of type k implies, from Equation (1), that

$$\frac{\partial crisis^k_{it}}{\partial top1nw_{it-2}} = \beta_1 + \beta_3 \left(\frac{W}{Y}\right)_{it-2} \lesseqgtr 0. \tag{3}$$

Coefficient β_1 is 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 would afflict β_2 if considering the marginal effects of aggregate wealth.) Hence the sign and significance of the overall marginal effect is emphasized, evaluated at the mean as well as the 25^{th} percentile of the wealth-income ratio distribution. Also presented is the average marginal effect of wealth inequality, whose standard errors are estimated using the Delta method. Plots of the individual marginal effects will provide a visual description of which sample observations are positive or negative.

Rejecting the null hypothesis $\mathcal{H}_1 : \beta_3 = 0$, in favor of a positive alternative where $\beta_3 > 0$, implies wealth inequality and aggregate wealth both contribute to financial instability so long as the expression in equation (3) remains greater than zero. It would support the structural interpretation, argued here, for why the distribution of stocks rather than flows contributes to the financial stability of an economy.

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

$$\frac{\partial crisis_{it}^{k}}{\partial(\frac{W}{Y})_{it-2}} = \beta_2 + 2\beta_4 \left(\frac{W}{Y}\right)_{it-2} + \beta_3 top1nw_{it-2} \lesseqqgtr 0. \tag{4}$$

Under this model, rejecting the null hypothesis $\mathcal{H}_2 : \beta_2 = 0 = \beta_4$ in favor of an alternative, in which $\beta_2 > 0$ and $\beta_4 < 0$ and generate a negatively sloped marginal effects curve, would suggest aggregate wealth displays an inverted U-shaped relationship with financial instability. A marginal effects curve that is positively sloped would contradict this claim.

While it may be tempting to summarize any marginal effect from wealth inequality on financial crises with a single statistic, such as an average marginal effect, doing so would be presumptive and assign too great a weight to preliminary analysis. Rather, the sign and significance is stressed.

3 Data

Wealth Inequality

The net worth held by the top 1% of households measures wealth inequality.[2] A survey by Roine & Waldenström (2015) collects ten national time series of wealth concentration.[3] Data

[2]Surveys from France, the UK, and US are based on individual data. Roine & Waldenström (2015) also cite studies comparing household versus individual surveys which find "no important differences."

[3]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)

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, the data are employed conscious of these shortcomings. Data begin with a single observation in 1740 for the UK and continue through 2012. Many series are sporadic with large gaps between observations. 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. 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.

It should be noted that US data are from the Kopczuk & Saez (2004) series rather than the more recent, and higher frequency, Saez & Zucman (2014) study. The latter's capitalization method, whereby top wealth shares are estimated using a multiplier that inflates reported capital incomes to national income and product account aggregates, is inconsistent with other countries in the panel. Later, when predicting probabilities at the individual country-level, the Saez & Zucman (2014) series are utilized.

Aggregate Wealth

Piketty & Zucman (2014) estimate a country's national wealth, calling it the capital-income ratio, by summing all marketable capital assets at their current price levels. This is equivalent to the aggregate wealth-income ratio. Assets tabulated 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.[4] It is supplemented with national wealth data estimates for Sweden (from Waldenström (2015)) and

[4]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/.

Denmark (from Abildgren (2015)).[5] Both series adhere to the methodological approach of Piketty & Zucman (2014). Some general trends emerge: all countries experience increases in aggregate wealth over the last 40 years, with some, such as the US and UK, 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 are notably approaching nineteenth century levels again—the contention of Piketty & Zucman (2014).

The 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, the panel contains up to 273 observations. However, it is quite 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. Indicator data come from Reinhart & Rogoff (2010), one such accepted source, and specify the country, year and crisis type. The authors define financial crises granularly, distinguishing between six crisis types.[6] The focus here is on two: banking crises and stock market crashes. (The others, it can be argued, are predominantly politically rather 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 the nine country panel, are summarized in a timeline in Figure A.1 in the online materials relative to the availability of explanatory variable observations. Existing continuous measures of financial stress are not considered because they only begin in the 1990s.

Controls

Myriad other factors, either at individual or aggregate levels, could account for any apparent

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

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

relationship between wealth inequality in rich countries and a financial crisis. 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, data on the overall share of value added to GDP by the financial sector over time are included. Data, from Philippon & Reshef (2013), begin as early as 1850 for some countries and continue through 2007.

From Roine et al. (2009), a measure of financial development (the sum of bank deposits and stock market capitalization) is included to estimate a proxy for the rate of return on capital, discussed in greater detail below. From the same study a measure of total private sector credit—as a share of GDP—accounts for borrowing by households and firms, the most cited determinant of financial crises in the literature. Data begin in 1900 and continue through 2006.[7] Top marginal tax rates are also included since they directly determine individual savings, which accumulate into wealth and can also represent a form of redistribution. Efforts at redistribution is cited as one destabilizing force of the US subprime mortgage crisis (Bordo & Meissner (2012) and Rajan (2011)).

Asset price bubbles, and the business cycles which generate them, are the prevailing economic theory for financial crises. To support the argument that it is the distribution of assets that contributes to financial instability, an attempt is made to control for these factors by including proxies for the rate of return on capital as well as GDP growth. Piketty (2014) presents $r > g$ as a simple theoretical relation between rates of return on capital and overall growth to explain long-run increases in wealth inequality, and Fuest et al. (2015) corroborate it empirically. Including both r and g helps to ensure that any apparent effect of wealth inequality on instability is not simply being driven by cyclical determinants of wealth inequality or asset price bubbles. Differencing over changes in financial development yields the proxy for r and g is approximated by the percent change in income per capita using Maddison-Project (2013 version) data. With the full set of control variables the panel data set becomes just 134 observations for 6 countries (Australia, Spain, France, Sweden, the UK, and US). (See Tables A.1–A.3 in the online supplementary materials. for summary statistics of explanatory and control variables.)

[7]See Table 1 in Roine et al. (2009) for detailed documentation of the original sources of each series.

4 Results

Ordinary least squares results are briefly discussed for various specifications of the reduced form linear probability model in equation (1). Of primary concern, however, is the marginal effect of wealth inequality on crises (Equations (3)). Inferring fitted probabilities is not practicable since in many instances values may be negative—and technically uninterpretable.

Results from estimating the likelihood of banking crises are presented in Table 1 and the likelihood of stock market crashes in Table 2. In the Panel A estimates of both crisis types, coefficients for the term interacting wealth inequality with aggregate wealth-income ratios are significant for the model specification only accounting for financial sector size (Columns 1). After careful consideration, balancing parsimony with sample size, but also by information criteria, this is the preferred specification. The preferred model explains over 57 percent of the variation in banking crises and 82 percent of the variation in stock market crashes. The estimated parameter for the interacted term retains significance, and increases slightly in magnitude, in the fully specified model (Columns 3).

[Table 1 about here.]

The parameter estimate for the interaction term between inequality and the wealth-income ratio in the stock market crash model (Table 2, Panel A) is notably more significant (at 1%) across all three specifications than the banking crisis models. One reason may be that the occurrence of a banking crisis is defined by government intervention, an inherently political and discretionary decision. Regulators and researchers may have varied definitions of a systemically important institution (which required the federal aid). Given 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 stronger inference exists in those models. The simplest explanation may just be the frequency of stock market crashes relative to banking crises in the data (see Table A.1 in the online supplementary material)—more than double.

[Table 2 about here.]

4.1 Marginal Effects

Independently, wealth inequality has a negative and significant (at 5%) coefficient concerning banking crises (Table 1, Column 1). Aggregate wealth has a similarly negative but insignificant coefficient. The marginal effect of wealth inequality on banking crises becomes

$$\frac{\partial crisis^b_{it}}{\partial top1nw_{it-2}} = -3.542 + 1.759\left(\frac{W}{Y}\right)_{it-2}, \tag{5}$$

and this expression is positive and increasing for all levels of the aggregate wealth-income ratio above the 0.02 percentile—that is, all observations in the full data series excluding three (Germany in 1948 and the UK in 1948–1949) and all observations in the subsample. The marginal effect of wealth inequality on banking crises is evaluated at two different points along the wealth-income ratio distribution, its mean and 25^{th} percentile. Additionally, the average of all individual marginal effects are also calculated. These results are summarized in Panel B of Table 1. A visual summary of the individual marginal effects is presented in Figure 1a, where the magnitude of the marginal effect is plotted against aggregate wealth levels, comparing observations across the entire sample of data with the specific subsample the preferred model (Column 1) was estimated on. The distribution of aggregate wealth observations is shown by the kernel density plot, where dashed vertical lines indicate medians. (Figure 1b summarizes the corresponding marginal effects of wealth inequality on stock market crashes in the same fashion.)

Importantly, the marginal effect of wealth inequality on the likelihood of a banking crisis is very positive, and significant at 1%, when evaluated at the average aggregate wealth value or when averaging the individual effects. In fact, the effect is positive and significant (at 5%) when evaluated all the way down at the 10^{th} percentile of the aggregate wealth distribution. In the fully specified model (Table 1, Column 3), which, while adjusting for relative rates of return, private credit, and marginal tax rates, reduces the sample size to 134 observations, the marginal effect of wealth inequality is even more positive, and remains significant at 5% when averaging across individual effects.

Turning to stock market crashes, the marginal effect of wealth inequality in the preferred model (Table 2, Column 1) is similarly positive in magnitude, increasing, and also significant at the 1% level. The explicit formulation becomes

$$\frac{\partial crisis^s_{it}}{\partial top1nw_{it-2}} = -6.964 + 2.459 \left(\frac{W}{Y}\right)_{it-2}. \tag{6}$$

It remains positive when wealth-income ratios are above the 8^{th} percentile of ratios among the model's full data series as well as its subsample (see Figure 1b), thus the marginal effect is positive at the mean and 25^{th} percentile of wealth-income ratios and significant to 1%. The same is true of the average marginal effect of wealth inequality on stock market crashes. While the fully specified model's estimates (Table 2, Column 3) are equally statistically significant, the marginal effect of wealth inequality on stock market crashes is positive only at and above the 15^{th} percentile of aggregate wealth in the subsample and the 20^{th} percentile of the full series. The marginal effects, after adjusting for credit, rates of growth, and tax rates, remain significant and significant at 1%.

[Figure 1 about here.]

Overall, the first null hypothesis ($\mathcal{H}_1 : \beta_3 = 0$) must be rejected. The alternative ($\beta_3 > 0$) is compatible with the network hypothesis: that wealth inequality positively contributes to financial instability in rich economies by arranging financial connections between individuals in an increasingly vulnerable organization. The LPM results indicate that wealth inequality has a positive and significant marginal effect on the likelihood of both of banking crises and stock market crashes. The positive slopes observed in Figure 1 support the contention that the marginal effect of wealth inequality on instability is increasing as economies become richer. While wealth inequality's marginal effect is positive on both crisis types, it is unsurprising that the stock market crash model's parameter estimates are more significant and consistent given their more objective definition and greater prevalence in the data. However, average marginal effects are similarly positive and significant between crisis types. These results support the argument that the distribution of wealth is an important component in determining the likelihood of some future financial crisis in a wealthy economy. The network framework implies that a rising maldistribution directly weakens the underlying interconnectedness of the economy such that a negative shock has a higher probability of inflicting contagion within a sufficiently rich network.

4.2 Additional Crisis Regressors

One concern with the above results is that they may be influenced by the seemingly random availability of historic wealth inequality observations. French wealth inequality data, for example, are available only every 10 years beginning in 1870. (See Figure A.1 online, which indicates crises and data observations in the largest subsample.) Another, more intractable problem, is that crises are correlated across countries. Considering these possibilities, more long-run relationships are examined by averaging observations across five-year horizons. The dependent variable now takes a value of 1 if the crisis type ever occurs over the half-decade interval, and a 0 otherwise. International correlations of crises may now be absorbed by the wider time window, and the wealth inequality-crisis relationship is framed in more of a long-run context. Lags are omitted in the averaged model.

Results from estimating the reduced form, two-way fixed effects models averaged across five-year intervals show consistently positive estimates for the interaction parameter. (See Tables B.4–B.5 online.) The fully specified model's estimates are most significant when describing the relationship to banking crises (Column 3), while the model adjusting for financial sector size, rates of return, and growth, and the fully specified model are most significant when describing the relationship to stock market crashes (Column 2–3).

For consistent comparisons to previous results, the preferred LPM model specification (Columns 1) is used to examine the marginal effects from wealth inequality (see Figure B.2 in the online material). 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. Specific marginal effects are summarized in Panel B of Table B.5 online. It shows that for each model specification, the average marginal effect of wealth inequality on stock market crashes is very positive and significant at at least 5%.

The marginal effect of wealth inequality is also positive on banking crises, though insignificant for the preferred model (see Panel B of Table B.4). It remains positive, but becomes significant (at 1%) in the fully specified model for all levels of aggregate wealth above the 25^{th} percentile in the subsample. The average effect of wealth inequality on stock market crashes is also positive and significant at 1% in the full model.

To further test the constancy of the wealth inequality-financial crisis relationship, the crisis indicator is redefined. A *large crisis* occurs when both crisis types occur within the same year for a given country (i.e. the intersection of banking crises and stock market crashes). Not only does such an indicator occur with much less frequency (only five percent of the largest subsample's observations), but it also reflects another popular crisis indicator developed by Schularick & Taylor (2012)—derived through peer-reviewed consensus as well as consultation with economic historians.

Regression results (presented in Table 3) indicate wealth inequality interacted with national wealth is significantly and positively related to large crises in the preferred specification, Column 1. Significance suffers attrition as controls are added and observations decline—though it remains significant at 10% in the full specification. Wealth inequality is found to have a positive and increasing marginal effect on the likelihood of large crises when aggregate wealth is anywhere above the 10^{th} percentile of the distribution in both the full sample and subsample of observations (see Figure 2). If all of the individual effects are averaged, the average marginal effect of wealth inequality on large crises is strongly positive and significant (at 1%) for each of the model specifications (Panel B, Table 3).

The averaging of observations over five year intervals is repeated for the *large crisis* indicator. Estimation results are shown in Table B.6 in the online supplementary material and are significant (at 1%) only in the fully specified model (Column 3). The overwhelming majority of observations yield a positive and increasing marginal effect of wealth inequality on the likelihood of a large crisis occurring for a given country in the preferred specification (see Figure B.3 online), however the small sample size of 72 observations limits inference.

[Table 3 about here.]

[Figure 2 about here.]

Together, these results support a strong positive relationship from rising wealth inequality to future financial instability, conditional on the aggregate wealth of the economy in question. Moreover, they are compatible with the contention that the distribution of accumulated assets imparts structural information about the economy which has direct implications for its macroeconomic stability. Unequally distributed assets imply an economic structure that is more vulnerable to contagion in rich economies.

4.3 Aggregate Wealth and Instability

The theoretical framework in Hauner (2016), in addition to linking wealth inequality to an increased likelihood of financial crisis, predicted an inverted U-shaped relationship between rising aggregate wealth and financial instability—echoing nonlinearities described in the financial network contagion literature. That is, as the network becomes wealthier instability increases but eventually decreases because a sufficiently high number of financial links between individuals absorb any negative shock and contagion threat. Least squares estimates of Equation (2) are presented in Table B.7 in the online supplementary material, all based on the preferred model specification that adjusts for financial sector size.

Though explaining between 50 and 80 percent of the variation in the data, and significant results (at 1%) for the interacted term between wealth inequality and aggregate wealth, no coefficient estimates of the wealth-income ratio terms suggest a plausible inverted-U relationship. In fact, the only estimates that actually lead to an inverted U-shaped relationship are from the stock market crash model, but it is upward sloping only for extremely negative values of aggregated wealth—an impossible situation—and decreasing for all nonnegative values. Thus the marginal effects of aggregate wealth on crises from Equation (4) are positively sloped—exactly the opposite of the anticipated outcome. (See Figure B.4 in the online appendix.) While some observations do yield a negative marginal effect, they do not reflect the predicted decreasing marginal effect.

Rejecting the second hypothesis ($\mathcal{H}_2 : \beta_2 = 0 = \beta_4$) still does not, however, favor an alternative that indicates a negative quadratic relationship between aggregate network wealth and instability as suggested by the hypothetical framework. One possibility is that the economies in the data have all attained sufficiently high levels of aggregate wealth by the 20^{th} century that they are all on the downward sloping portion of an inverted-U curve. The large proportion of observations that show a significantly negative marginal effect of aggregate wealth on stock market crashes (Figure B.4b) leaves this preliminary analysis incomplete.

5 Robustness Checks

This section presents findings on and discusses three robustness checks of the empirical results. First, the empirical relationship in Equation (1) is estimated with a fixed effects logit model. Second, income is substituted for wealth as the inequality measure to test if the distribution of stocks does in fact have more explanatory power than the distribution of flows. Lastly, predicted probabilities of logit models are compared, on a country-by-country basis, with actual large crisis episodes.

5.1 Fixed Effect Logit

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

$$\Pr(crisis_{it}^{k} = 1) = \Lambda\left[\delta_i + \beta_1 top1nw_{it-2} + \beta_2 \left(\frac{W}{Y}\right)_{it-2} + \beta_3 top1nw \times \left(\frac{W}{Y}\right)_{it-2} + \gamma'\mathbf{X}_{it-3}\right], \quad (7)$$

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

Results estimating the likelihood of banking crises, stock market crashes, and large crises are shown in Tables C.8–C.10 in the online material. In the preferred models (Column 1), estimates are not significant—though the interacted term between inequality and wealth remains positive. The fully specified models become significant and extremely positive in the interacted term, however extremely large standard errors suggest the specification is overdetermined. (The fully specified large crisis model is, in fact, perfectly determined.)

Estimating the marginal effects of wealth inequality on both crisis types yields the plots in Figures C.5–C.6 online, both based on the specification in Columns 1. Marginal effects from wealth inequality are overwhelming negative, though increasing, on banking crises. The effects on stock market crashes and large crises, however, are overwhelmingly positive. The average of the individual marginal effects is positive and significant at 1% in the second and third specifications of the stock market crash model and second specification of the large crisis model.

5.2 Income Inequality

Is the emphasis on wealth inequality rather than income inequality warranted? Or, does income inequality also relate to future unstable financial markets? The same reduced form linear probability model with two-way fixed effects in Equation (1) is estimated by simply substituting top income shares data for top wealth shares data. Income inequality data are more common, so the panel expands to 10 countries with a maximum of 538 observations.

Estimation results are presented in Tables D.11 and D.12 in the online supplementary material. The impact of income inequality on financial instability is ambiguous and insignificant. Parameter estimates of 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.

Though insignificant, the marginal effects of income inequality are also analyzed. As a comparison to Figure 1 above, individual effects are estimated for all observations in the full sample of wealth-income ratios and the subsample the preferred wealth-inequality specification was estimated on (Column 1). (See Figure D.7 online). The effect is generally positive and increasing for banking crises, and the average effect is positive and significant to 5%. However, the average marginal effect of income inequality on banking crises in the fully specified model, while insignificant, is negative and of comparable magnitude.

The income inequality model of the likelihood of stock market crashes is entirely insignificant, and its marginal effects are entirely negative. While the marginal effects are increasing, they are decidedly negative, both individually and on average.

A Davidson & MacKinnon (1981) J-test of model specification confirms the lack of explanatory power for income inequality in either financial crisis model.[8] These results further support the hypothesis, and preliminary statistical evidence presented above, that the unequal distribution of financial assets (a stock) rather than incomes (a flow) positively influences a wealthy economy's likelihood of future financial crisis.

5.3 Predictions

While the sign and significance of marginal effects have been stressed, the relationship between aggregate wealth and its distribution should correspond to actual financial crisis episodes in keeping with the hypothetical network relationship. That is, the models' within-sample predicted probabilities should correspond to actual crises for a given country. To generate these forecasts a logit model is used so that predicted values are constrained to the unit interval and have clear interpretations. Estimating equations country-by-country necessarily eliminates country fixed effects. (Including year fixed effects only yields perfectly determined outcomes.)

The limitations of the aggregate wealth and wealth inequality data imply that it is possible to estimate predictions for only four countries: the United States, United Kingdom, Denmark, and Sweden. In order to extend the time series from 2000 through 2012 for the United States, wealth inequality data now come from Saez & Zucman (2014), who use the capitalization estimation method, rather than Kopczuk & Saez (2004), who use the estate tax method.

The preferred model specification is used whenever possible:

$$\Pr(crisis_{it}^{k}=1)=\Lambda\left[\alpha+\beta_1 top1nw_{it-2}+\beta_2\left(\frac{W}{Y}\right)_{it-2}+\beta_3 top1nw\times\left(\frac{W}{Y}\right)_{it-2}+\beta_4 finsh_{it-2}+\varepsilon_{it}\right] \tag{8}$$

To judge to accuracy of the above model, predicted probabilities are compared against the lagged real-changes-in-credit model of Schularick & Taylor (2012), henceforth S&T, a oft-cited model in

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

the literature:[9]

$$\Pr(crisis_{it}^{k} = 1) = \Lambda \left[\alpha + \sum_{k=1}^{5} \beta_k \Delta \ln rcredit_{it-k} + \varepsilon_{it} \right]. \tag{9}$$

Two crisis indicator variables are compared. The first is the *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 crisis indicator comes from S&T and omits some large crises but also includes additional ones, thus differing from the exact Reinhart & Rogoff dates.

Results are presented graphically in Figure 3 below (large crises), as well as in the online supplementary material (S&T crises and Swedish and Danish outcomes). Plotting each individual predicted probability helps to illustrate the relative sparsity of some country-level data. Vertical grey bars represent a relevant crisis year. In the case of Sweden, the preferred model (Equation (8)) can not be estimated since financial sector share values greater than 0.062 predict the outcome perfectly—thus the $finsh$ term is dropped. And in the case of Denmark, no crises occur for the subsample of observations for which financial sector share data are available—so again, the $finsh$ term is dropped.

[Figure 3 about here.]

The preferred model clearly outperforms the S&T model in the case of large crises in the United States (Figure **??**). It appropriately peaks during the Great Crash, recedes during the postwar period, and then slowly increase beginning in the late 1980s with spikes in 1990 and the late 1990s and mid 2000s. Equation (8) is particularly nuanced in tracing economic instability in anticipation of the dot-com bubble, itself not categorized as a large crisis, and again near 2006, to presage the eventual subprime mortgage crisis. The preferred model performs equally well to predict instability as defined by S&T crises (see Figure E.8 online), climbing dramatically in 2000 and 2001, declining somewhat, and then peaking before the recent global financial crisis. An earlier peak coincides with the Great Crash, an S&T coded crisis. By comparison the S&T model is too volatile, equally for the crises the model was designed for and the large crises as defined in this paper. Its relative

[9] For example, Kumhof & Ranciere (2010) use it to estimate the level of endogenous financial instability created through inequality and leverage.

changes in probability reflect business cycles more than any genuine financial stability risk, and peaks in predicted probabilities all occur away from any crisis episode. In other words, the S&T model cries wolf. One simple reason for the success of the preferred model for the US is that there exist a large number of observations (98 and 95) from which to estimate.

The United Kingdom case also lends credibility to the preferred model, again in both large crises (Figure **??**) as well as S&T defined crises (Figure E.8), despite having only 60 or 64 observations from which to estimate. Predicted probabilities increase steadily, with a relative peak, near the 1973 oil embargo crisis. They also increase before the S&T defined crises of 1984 and 1991 and then increase again in anticipation of the global financial crisis in 2007. The S&T model still exhibits tremendous volatility, again crying wolf during eras of relative financial market tranquility.

The Danish and Swedish models predicting large crises (Figure E.9) perform poorly by comparison, which is understandable given the irregular and infrequent data—only 38 and 31 observations, respectively. The peaks at the beginning of the predicted series appear to correspond to crisis episodes, however, the models completely miss on the recent global financial crisis, lacking any foresight. Of course the paucity of Danish data since 1980 are one important factor. The Swedish predictions do correlate with the real estate crisis in the early 1990s, however the relative increase in probability is recent and obfuscated by probabilities of similar magnitude 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, the empirical results are consistent enough to lend support to the 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 the paper’s empirical approach is a radically simplified interpretation of a financial network 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.[10] The distribution of wealth therefore acts as a sufficient statistic to describe the arrangement of linkages in a networked financial economy. 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. Contagion will be greater, simulations show. 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 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 the logit models, particularly the US and UK cases, gives further support to network theory interpretation. 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).

These empirical 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

[10] See Hauner (2016).

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 continued study. First and foremost is the overall paucity of wealth inequality data. While annual top wealth share estimates exist for the United States under numerous methodologies,[11] 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.

As the survey Morelli & Atkinson (2015) concludes, context is key to any relationship between inequality and crisis in a given country. "It might not be an iron law," they warn. It may even be that global inequality, given the interconnectedness of all financial markets, may be the most relevant for contemporary financial crises—another area for future study.

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

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Table 1: Likelihood of Banking Crisis

Panel A			
	(1)	(2)	(3)
Top 1% Shr Net Worth $_{t-2}$	-3.542*	-0.699	-1.807
	(1.757)	(2.536)	(2.388)
Wealth-Income ratio $_{t-2}$	-0.169	-0.110	-0.227
	(0.185)	(0.217)	(0.233)
Top 1% Shr Net Worth × Wealth-Income ratio $_{t-2}$	1.759**	1.350	2.031*
	(0.565)	(1.024)	(0.901)
Finance Shr of Income $_{t-2}$	-6.077	-8.543	-8.463
	(6.440)	(5.382)	(5.435)
$\tilde{r}$ $_{t-2}$		-0.038	0.045
		(0.256)	(0.295)
$\hat{g}$ $_{t-2}$		1.148	-0.108
		(1.027)	(1.224)
Private Sector Credit $_{t-2}$			0.065
			(0.104)
Top Marginal Tax Rate $_{t-2}$			-0.007*
			(0.003)
Panel B			
Marginal Effects of Top 1% Shr Net Worth			
at Mean of Wealth-Income ratio	3.837***	4.865*	6.374*
	(1.097)	(2.177)	(2.503)
at P25 of Wealth-Income ratio	3.057**	4.530**	5.971*
	(0.934)	(1.958)	(2.371)
Average Marginal Effect			
	3.837***	4.865**	6.374**
	(1.097)	(2.177)	(2.503)
AIC	-18.6	-3.6	-10.3
R^2	0.571	0.528	0.565
Countries	9	9	6
Obs	213	156	134

Clustered standard errors in parentheses of Panel A

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

Notes: Dependent variable is a binary indicator of banking crisis in a 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. Panel B depicts marginal effects of wealth inequality on the crisis type when evaluated at the mean and 25^{th} percentile of aggregate wealth as well as the average marginal effect.

Table 2: Likelihood of Stock Market Crash

Panel A			
	(1)	(2)	(3)
Top 1% Shr Net Worth $_{t-2}$	-6.964***	-8.638***	-9.465***
	(0.668)	(1.448)	(2.173)
Wealth-Income ratio $_{t-2}$	-0.602***	-0.622***	-0.772**
	(0.066)	(0.124)	(0.219)
Top 1% Shr Net Worth × Wealth-Income ratio $_{t-2}$	2.459***	2.733***	2.892***
	(0.210)	(0.599)	(0.696)
Finance Shr of Income $_{t-2}$	9.036**	9.366*	7.540
	(3.423)	(4.070)	(5.257)
$\tilde{r}$ $_{t-2}$		-0.395*	-0.379
		(0.197)	(0.257)
$\hat{g}$ $_{t-2}$		-0.012	-0.703
		(1.346)	(1.615)
Private Sector Credit $_{t-2}$			0.063
			(0.143)
Top Marginal Tax Rate $_{t-2}$			-0.003
			(0.007)
Panel B			
Marginal Effects of Top 1% Shr Net Worth			
at Mean of Wealth-Income ratio	3.353***	2.624*	2.184**
	(0.454)	(1.205)	(0.677)
at P25 of Wealth-Income ratio	2.262***	1.945	1.610**
	(0.397)	(1.070)	(0.548)
Average Marginal Effect			
	3.353***	2.624**	2.184***
	(0.454)	(1.205)	(0.677)
AIC	-101.6	-53.1	-65.4
R^2	0.825	0.772	0.794
Countries	9	9	6
Obs	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 stock market crash in a 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. Panel B depicts marginal effects of wealth inequality on the crisis type when evaluated at the mean and 25^{th} percentile of aggregate wealth as well as the average marginal effect.

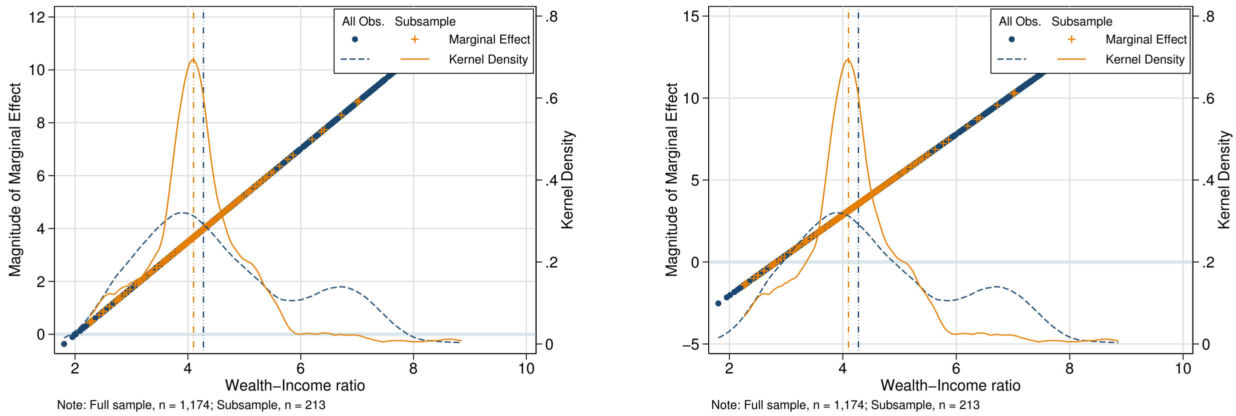
Table 3: Likelihood of Large Crisis

Panel A	(1)	(2)	(3)
Top 1% Shr Net Worth $_{t-2}$	-6.847***	-3.872*	-3.831
	(1.071)	(1.964)	(2.361)
Wealth-Income ratio $_{t-2}$	-0.517***	-0.401**	-0.369
	(0.096)	(0.154)	(0.196)
Top 1% Shr Net Worth × Wealth-Income ratio $_{t-2}$	2.343***	1.769**	1.935*
	(0.386)	(0.743)	(0.904)
Finance Shr of Income $_{t-2}$	3.846	2.607	6.643*
	(2.267)	(2.733)	(2.856)
$\tilde{r}$ $_{t-2}$		-0.117	-0.264
		(0.271)	(0.416)
$\hat{g}$ $_{t-2}$		-0.698	-1.666
		(1.550)	(2.073)
Private Sector Credit $_{t-2}$			-0.168*
			(0.083)
Top Marginal Tax Rate $_{t-2}$			-0.008*
			(0.003)
Panel B			
Marginal Effects of Top 1% Shr Net Worth			
at Mean of Wealth-Income ratio	2.981***	3.418**	3.965**
	(0.709)	(1.275)	(1.355)
at P25 of Wealth-Income ratio	1.942***	2.978**	3.581**
	(0.569)	(1.109)	(1.183)
Average Marginal Effect			
	2.981***	3.418***	3.965***
	(0.709)	(1.275)	(1.355)
AIC	-187.2	-146.2	-131.4
R^2	0.511	0.406	0.406
Countries	9	9	6
Obs	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 *both* a banking crisis and a stock market crash in a 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. Panel B depicts marginal effects of wealth inequality on the crisis type when evaluated at the mean and 25^{th} percentile of aggregate wealth as well as the average marginal effect.



(a) Banking Crisis

(b) Stock Market Crash

Figure 1: Marginal Effect of Wealth Inequality on Likelihood of Crisis

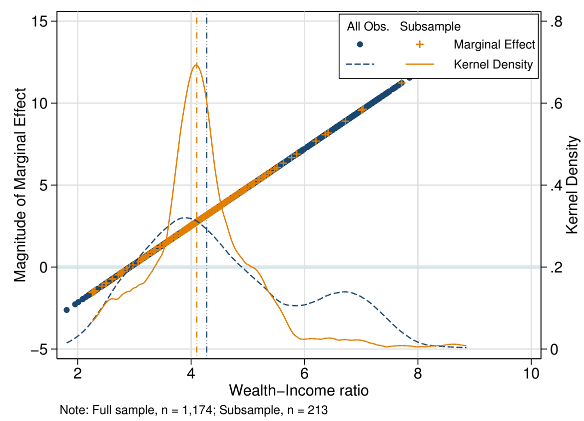
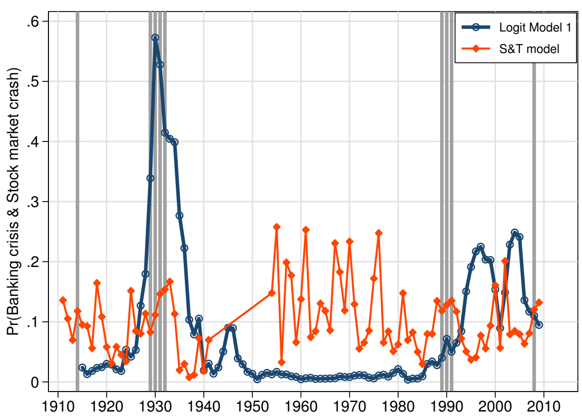
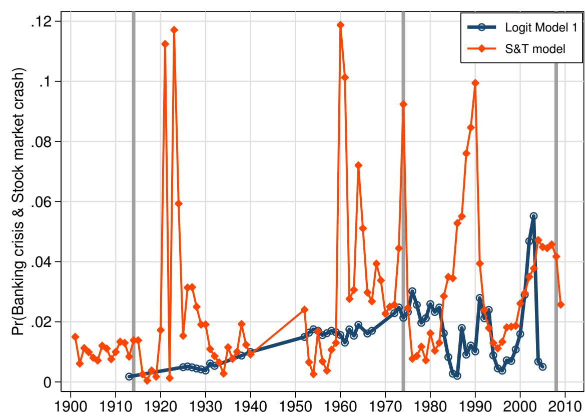


Figure 2: Marginal Effect of Wealth Inequality on Likelihood of Large Crisis



(a) United States



(b) United Kingdom

Figure 3: Predicted Probabilities of Large Crisis