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 remains ambiguous in the literature, evidence is presented suggesting a positive relationship between the interaction of wealth inequality with aggregate wealth on systemic financial crises. The evidence is based on panel data for nine countries, some of which expand into the last century, and a linear probability model estimated with country and year fixed effects. The relationship is consistent when accounting for overall financial sector size, credit growth, the money supply, current account, asset bubbles, and robust to estimation method. No significant role is found for income inequality. Predicted probabilities of financial crisis closely track the incidence of financial crises over the last century, remarkably so when compared against a leading benchmark model. It is argued that the empirical relationship between wealth inequality, aggregate wealth and financial crises reveals 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 the empirical results.

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

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1 Introduction

Familiar plots from Thomas Piketty and Emmanuel Saez reveal the share of both income and wealth held by top percentiles in the United States provocatively peaking before both the Great Crash and the Global Financial Crisis. (For example, see Alvaredo et al. (2013) and Saez & Zucman (2016).) This correlation has generated much discussion and research into the relationship between income inequality and financial crisis. (See Milanovic (2009), Krugman (2010), Acemoglu (2011), Bordo & Meissner (2012), Malinen (2016), and Kirschenmann et al. (2016) among others.) However, any role for wealth inequality has not been studied closely.

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 and significant effect on the likelihood of a systemic financial 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, linear probability models with two-way fixed effects. The results hold when accounting for financial sector size, private sector credit, broad money, and asset bubbles in stocks and housing, among other controls. The results are also robust to excluding the 2007 Global Financial Crisis from the data sample as well as estimation method. No significant relationships, however, are found when income inequality replaces wealth inequality in the model. Furthermore, the empirical model interacting wealth inequality with aggregate wealth is found to be a strong predictor of financial crises. This empirical finding suggests that wealth inequality and aggregate wealth in tandem capture certain structural attributes of the economy that income inequality does not. And some structural arrangements are more stable than others.

Why might the distribution of assets (a stock) be a more relevant determinant of financial instability than the distribution of income (a flow)? Asset accumulations can serve as a proxy for the underlying structure of relationships between creditors and debtors. Axel Leijonhufvud once 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 (2017), using a simple static network model of interpersonal wealth, it is shown that wealth inequality, when moderated by aggregate wealth, can determine the stability of the economy in the event of a shock. Stability is measured by the proportion of the network economy whose net worth drops below some relative threshold. When financial 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 financial assets are unequally distributed, and there are a sufficient number of them in the economy, a shock is less likely to be absorbed by the network. Across model simulations, network contagion is jointly determined by the level of wealth inequality and total wealth.

The primary mechanisms in the literature used to explain the association between inequality and financial crises only consider income inequality and the most recent crisis, not wealth inequality or a long-run view. One variation, a demand side narrative, argues 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. 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)). Kumhof & Ranciere (2010) argue that the precise causal force of growing debt is less concerning since many forces contributed (e.g. weakened labor bargaining positions, stunted income growth, and the search for yield amongst wealthy households). What matters is the equilibrium level of household debt, which contributes to instability by increasing leverage in the economy. Lucchino & Morelli (2012) provide a summary of the existing theories and highlight which parts of the income distribution each emphasizes. None, however, consider the wealth distribution.

The household debt mechanism interpreted only through income inequality is therefore incomplete for two reasons. 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—the period most frequently studied. 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, and most important, debt is the corollary of the true structural forces driving economic instability. 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. Precisely because one individual's liability is another's asset, the empirical focus of this paper turns to the latter half of the balance sheet. It is argued that wealth inequality and aggregate wealth, rather than income inequality, is not only the more influential determinant of financial crises but also a reasonable predictor of them.

The remainder of the paper is organized as follows: Section 2 outlines the reduced-form econometric model, 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 presents predictions of crisis probabilities for three countries. Section 7 interprets the empirical findings through a theoretical framework, the network model, and Section 8 concludes.

2 Methodology

A reduced-form empirical model is presented in this section based on insights from the financial crises and income inequality literature. There, the dominant framework is a logit model estimating some binary indicator of financial crisis as a function of lagged variables. Country fixed effects are typically included to highlight within-country variation and control for time-invariant heterogeneity. Year fixed effects, however, have not been employed. This omission is primarily because of the theoretical and computational challenges of solving the incidental parameter problem for nonlinear models.[1] While solutions have been proposed (see Charbonneau (2017) for an elegant solution and Cruz-Gonzalez et al. (2017) for bias correction using an alternative method) they have only recently begun to be implemented in applied settings, and were either unavailable or did not converge in this analysis. A previous alternative, including year dummies as a time fixed effect in a conditional logit model, drops all observations lacking variation in the dependent variable and leaves too small a sample when studying infrequent events like financial crises.

Instead, this paper applies the linear probability model (LPM) as it allows the econometrician to control for both common aggregate shocks with year fixed effects, as well as time-invariant heterogeneity using country fixed effects. Because there 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 1, below), it becomes important to control for both time and country fixed effects as allowed by the LPM as the results are then derived from within-country variation that excludes any common time-varying shocks. Employing both is straightforward and robust standard errors are used throughout, clustered at the country level. The linear model's chief limitation with binary dependent variables is that predicted values are not constrained between zero and one. Depending on the model's application, forecasts of probabilities may be illogical or uninterpretable, that is, negative or greater than one.

This paper's focus is testing the role that aggregate national wealth and its distribution play together in contributing to financial crises. The underlying intuition is that a country must be sufficiently wealthy before high wealth inequality can threaten financial and economic stability. To test for the joint significance, a binary financial crisis indicator is regressed on wealth inequality, or wealth concentration, $top1nw$, the aggregate national wealth-income ratio W/Y, and their interaction.

In each of the linear probability model specifications, variables are in first differences to exclude

[1] The incidental parameter problem refers to the phenomenon when, in nonlinear models with a fixed number of observations for each group, the fixed effect estimate bias distorts estimates for the parameter of interest.

any stochastic or deterministic trends. (There is no clear consensus on the stationarity of inequality series or aggregate wealth at the country level.) Including top wealth shares in levels, given varying methodologies employed in the panel data, could also bias results.

The linear probability model thus takes the following form, including country and year fixed effects:

$$\begin{aligned} crisis_{it} =& \beta_1 \Delta top1nw_{it-1} + \beta_2 \Delta \left(\frac{W}{Y}\right)_{it-1} + \beta_3 \left(\Delta top1nw \times \Delta \frac{W}{Y}\right)_{it-1} \\ &+ \phi' \mathbf{\Delta X}_{it-1} + \alpha_i + \gamma_t + \varepsilon_{it}. \end{aligned} \tag{1}$$

The binary financial crisis indicator $crisis_{it}$ describes a financial crisis event in country i and year t. The vector $\mathbf{X}$ contains a set of control variables including financial sector size, estimated averages rates of return on equities and house prices, average GDP per capita growth rates and other covariates discussed in detail in the following section. Lag-length, included to clarify the direction of the proposed relationship, is initially one period, but alternative lengths for different variables are also considered.[2]

Though the preference is to control for both country and year fixed effects, as a robustness exercise conditional logit models are estimated in Section 5 that only control for country fixed effects. Additionally, LPM estimations on varying subsamples of the data, in order to challenge the dominance of particular crisis events or availability of particular country data, are also presented along with a test of income inequality's significance in the relationship.

3 Data

Wealth Inequality

Wealth inequality, or concentration, is measured as the net personal wealth held by the top 1% of households or individuals. Data for France, Great Britain and the US measure top wealth

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

shares for individuals and come from three primary sources. The Wealth Inequality Database (WID) (Alvaredo et al. (2018)), using the distributional national accounts (DINA) methodology that accounts for 100 percent of national incomes rather than just 60 percent from fiscal data, provides data for France, Great Britain and the US. The DINA method, which estimates top wealth shares by using a multiplier that inflates reported capital incomes to national account aggregates, was first applied to US capital incomes to measure wealth concentration in Saez & Zucman (2014) and has since been applied to other countries in Alvaredo et al. (2017).

Wealth inequality data for Australia, Denmark, the Netherlands, Norway, Sweden and Spain are all measured by household. Roine & Waldenström (2015) provide data for Australia, Denmark, the Netherlands, Norway and Sweden (whose data are for individuals after 2000). The authors document the specific mix of data sources, both fiscal and survey and often a combination of the two.[3] Spanish wealth inequality data originate from Alvaredo & Saez (2009) who rely on fiscal data. A more recent study by Toledano et al. (2015) using the capitalization method applied in the DINA data, finds the earlier Spanish data underestimate wealth inequality for overlapping observations. Each country's time series is dependent on survey sampling methods and weighting, tax evasion, mortality rate calculations, as well as the basic unit of measurement.

Despite heterogeneous methods, but also given the lack of a single consistent historical survey across countries, the data are employed conscious of these shortcomings. Data begin with a single observation in 1740 for Great Britain 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 in the 1970s. Australia, Sweden, and Great Britain show moderate increases over the last 40 years, while others are more severe such as France and the US, which is the only country to approach early twentieth century levels. Because the competing methods of using fiscal, survey, and national accounts can lead to differences in levels, the variable, and all others in the analysis, are differenced in the model.

A clear example of the impact of methodology on wealth inequality measurements is the case

[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).

of the US, where estate tax data used by Kopczuk & Saez (2004) understates the level compared to the capitalized fiscal and national accounts data used by Saez & Zucman (2014) and now the WID. The capitalization method arguably accounts for the phenomenon of tax evasion amongst top wealth shares documented in Alstadsæter et al. (2017).

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 are now available as part of the WID from Alvaredo et al. (2018) and cover a panel of nine countries, beginning as early as 1845 and continuing through 2012. These data are supplemented with national wealth data estimates for Denmark from Abildgren (2015), who adheres 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 Great Britain, beginning around 60 years ago; all countries, except Sweden and the US, had very high aggregate wealth in the nineteenth century; and Great Britain 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 after taking first differences: Australia, Denmark, France, Great Britain, the Netherlands, Norway, Spain, Sweden, and the US. Depending on model specification and estimation method, the panel contains up to 428 observations. However, it is quite unbalanced. There exist 123 unique years, starting in 1875 and continuing through 2014, but no year contains all nine countries and only about one-third of the years contain five or more countries.

Financial Crises

Binary financial crisis indicators invite scrutiny since they are largely determined through professional consensus, established through precedent and acceptance in the relevant economic history literature. The financial crisis data come from Jorda et al. (2017), and their newly compiled Macrohistory database, which builds off of the cumulative list of financial crises in Reinhart & Rogoff (2010). Both have become definitive sources, and specify the country, year and type of crisis. The Macrohistory database focuses only on systemic financial crises, defined as "events during which a country's banking sector experiences bank runs, sharp increases in default rates accompanied by large losses of capital that result in public intervention, bankruptcy, or forced merger of financial institutions." Reinhart & Rogoff (2010) define financial crises granularly, distinguishing between six crisis types: currency, inflation, stock market crashes, domestic and external sovereign debt, and banking crises. A timeline in Figure 1 plots the systemic financial crisis events relative to the availability of explanatory variable observations. In the online supplementary materials, Table A.1 presents the total number of systemic crises and observations by country.

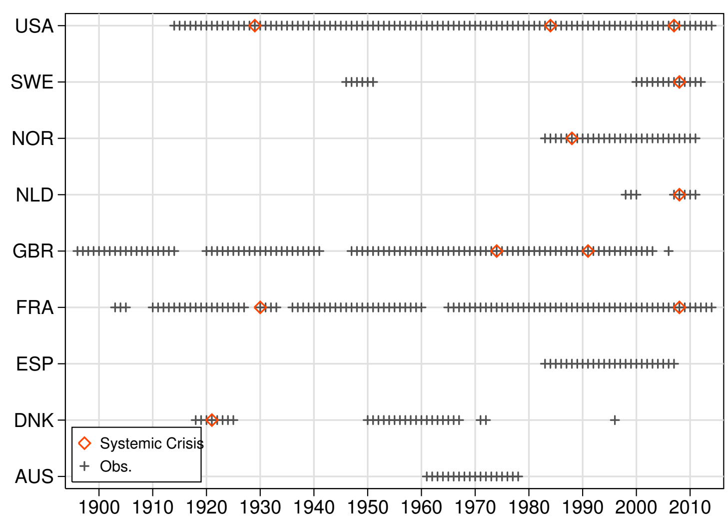


Figure 1: Financial Crises and Data Observations
Notes: Sub-sample restricted to country-year observations with data on both top 1% wealth shares and aggregate wealth-income ratios.

Control Variables

Numerous sets of control variables are included to help eliminate competing narratives from the financial crisis literature in favor of the proposed wealth inequality and aggregate wealth interaction. (The role of income inequality is considered separately as a robustness check.) 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. After including aggregate wealth and top wealth share data, however, only Great Britain and the US have long-run data samples. (Figure A.1 in the online supplementary materials visualizes how this control variable curtails the sample.)

Asset price bubbles, and the business cycles which generate them, are the prevailing economic theory for financial crises. 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. Controlling for 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. The rate of return r is proxied by differenced nominal stock price indices, in logs, and the growth rate g is proxied by differenced real GDP per capita, also in logs.

In a working paper, Kiley (2018) argues that not only asset valuations but also the current account deficit are more valid predictors of financial crises, particularly during the post-war period. The inclusion of the aforementioned rate of return proxy helps to control for equity asset valuations as a contributing factor, and the inclusion of a differenced nominal housing price index (from Knoll et al. (2016)), in logs, helps to control for housing asset valuations. Current account deficits, however, are the most significant driver of crises, Kiley argues, and thus the real current account is added to control for this alternative hypothesis.

Borio & Disyatat (2011) argue that to focus on the current account balance is misguided because the current account captures net flows, or saving. Instead, they argue, financing decisions are about gross financial flows and therefore broad money is added as a control variable—what others consider a more meaningful engine of excess credit growth.

The conventional hypothesis of financial crises is the credit narrative best characterized by Schularick & Taylor (2012), in which excess credit growth heightens the instability of the financial economy. Three varying measures of real credit are included to control for the conventional narrative. First, total real bank loans to the non-financial private sector are included, Schularick & Taylor's preferred credit measure. Second, broad money, as mentioned above, and third, real investment, which may capture some aspects of productive credit growth that total real bank lending omits. Each of the three variables is log-transformed and first-differenced.

Lastly, to control for the possibility that unexpected shifts in interest rates may provoke or catalyze a financial crisis, differenced short-term nominal interest rates are added with the final set of credit control variables. Aside from financial sector size, each of the control variables come from Jorda et al. (2017) and their Macrohistory database.

With the full set of control variables included the panel data set includes 313 observations for nine countries (Australia, Denmark, France, Great Britain, the Netherlands, Norway, Spain, Sweden, and the US). Because its wealth inequality measurements are taken every other year, first-differencing of observations eliminates Italy from the sample. Considering only the explanatory variables, wealth inequality and aggregate wealth, the panel includes 428 observations. See Table A.2 in the online supplementary materials for summary statistics of explanatory and control variables.

4 Results

Ordinary least squares results from the reduced form linear probability model in Equation (1) are presented below. Of primary interest is the relationship between the interaction of wealth inequality with aggregate wealth and systemic financial crises. Later, in Section 6, within-sample and out-of-sample predictions of the LPM are presented as further evidence of the estimated model's validity.

Results from estimating the likelihood of systemic financial crises are shown in Table 1. The models specified in each column correspond to the inclusion of varying sets of control variables, each an attempt to account for alternative hypotheses concerning the probability of financial crises. The first model, Column 1, excludes the explanatory variable of interest, the interaction of top wealth shares and wealth-income ratios, and simply tests if there is any meaningful direct relationship between either wealth inequality or aggregate wealth and financial crises. There is not. The sign on both parameters is negative, though they fluctuate in later specifications. They are also both insignificant, and remain so.

Table 1: Likelihood of Systemic Financial Crisis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Top 1% Shr Net Worth $_{t-1}$	-0.099	-0.075	0.090	-0.024	0.070	-0.095	0.057	0.308
	(0.664)	(0.650)	(1.006)	(0.677)	(0.636)	(0.593)	(0.602)	(1.016)
Δ Wealth-Income Ratio $_{t-1}$	-0.008	0.005	0.023	-0.006	-0.010	-0.001	0.002	-0.002
	(0.019)	(0.021)	(0.049)	(0.027)	(0.028)	(0.024)	(0.021)	(0.078)
(Δ Top 1% Shr Net Worth $\times$ Δ Wealth-Income Ratio) $_{t-1}$		3.808*	6.249	3.986*	3.535**	4.172**	2.694*	6.785**
		(1.915)	(3.449)	(1.938)	(1.356)	(1.599)	(1.360)	(2.427)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Finance Share			✓					✓
Stocks, Housing, $\hat{g}$				✓	✓			✓
Current Account					✓			✓
Broad Money, Real Bank Loans						✓	✓	✓
Real Investment, Short Term Int. Rate							✓	✓
AIC	-532.5	-537.0	-340.6	-523.3	-523.8	-508.1	-531.0	-337.3
BIC	-500.0	-504.5	-310.5	-491.0	-491.8	-476.0	-499.0	-307.4
R^2	0.396	0.403	0.417	0.406	0.417	0.410	0.415	0.426
Countries	9	9	9	9	9	9	9	9
Obs	428	428	317	421	402	413	406	313

Clustered standard errors in parentheses

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

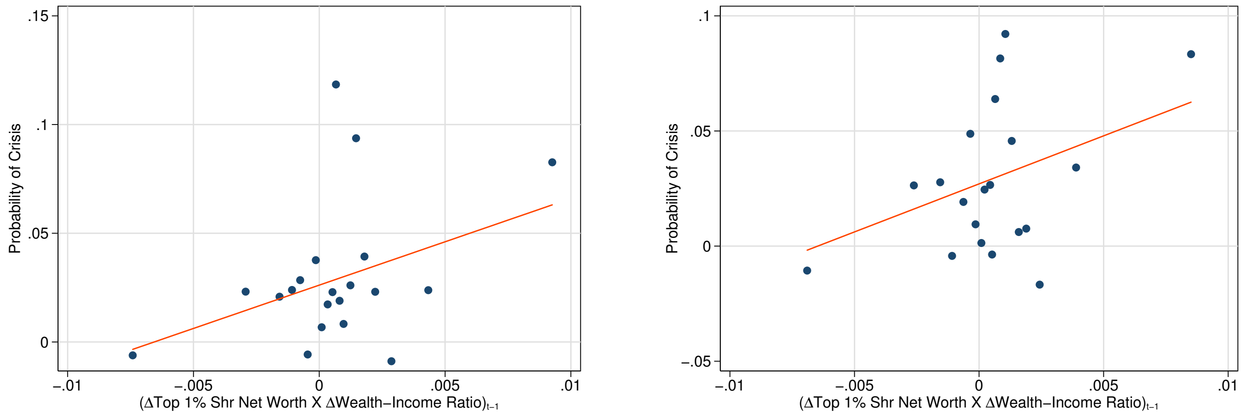
Notes: Dependent variable is a binary indicator of a systemic financial crisis event for a given country-year observation. The linear probability model is estimated with two-way fixed effects (2FE), controlling for country and year. Control variables are all lagged first differences and include the financial sector's share of GDP, the logs of stock price and home price indices, a growth proxy (real GDP per capita), the logs of the real current account, broad money and total real bank loans to the non-financial private sector, the log of real investment, and the short-term interest rate. All controls variables come from Jorda et al. (2017) with the exception the financial sector's share, which comes from Philippon & Reshef (2013).

Beginning with the model in Column 2, the explanatory variable of interest, the interaction of wealth inequality and aggregate wealth, is included and it is strongly positive and significant. This is the key empirical result, indicating wealth inequality positively contributes to the likelihood of financial crises but only when moderated by an economy's high aggregate wealth. The inclusion of the financial sector size control in the model in Column 3 removes the significance of the interaction term while its magnitude nearly doubles. One reason for this might be the fact that financial sector size data are only available for Great Britain and the US for sufficiently long periods, (beginning in 1875 and 1813, respectively), and thus the two countries bias the results as the variable's inclusion shrinks the sample by nearly one quarter. The insignificance is not entirely disconcerting because when all controls are added in the final specification in Column 8, including financial sector size, the interaction term is very positive and significant.

Continuing with the other model specifications in Table 1, Column 4 both controls for the asset valuation hypothesis by including percent changes in stock and house price indices (both lagged, like each control variable) as well as Piketty's $r > g$ hypothesis as a long-run driver of wealth inequality. The interaction term is positive and significant, and its magnitude comparable to the baseline specification in Column 2. The additional control of the real current account, in Column 5, increases the significance while the magnitude is roughly the same.

Model specifications in Columns 6 and 7 consider the prevailing hypothesis that excessive credit or monetary expansion are the main determinants of financial crises. The inclusion of only broad money and real bank loans do nothing to diminish the magnitude or significance of the interaction term. Wealth concentration moderated by the wealth-income ratio continues to be highly positively related to future financial crises. Adding controls for real investment and the short-term interest rate, in Column 7, diminishes the magnitude of the effect of the interaction term, however it remains significant.

The final specification, in Column 8, considers all of the control variables together. The significance of the interaction term between wealth inequality and aggregate wealth remains and its magnitude increases—much like in Column 3, the other specification that includes the financial sector size variable. Full regression results, with parameter estimates for all control variables, are available in the online supplementary material in Table B.3. The only statistically significant control is the financial sector's share of GDP, included in Columns 3 and 8.



(a) Model specification 5 **(b)** Model specification 7

Figure 2: Linear relationship between the interaction of wealth inequality with aggregate wealth and financial crises

The preferred model specification is Column 7, which controls for the predominant credit growth hypothesis of crises. This preference is based upon information criteria, fit, parsimony, and the relevance of the control variables. Equally important is that its out-of-sample predicted crisis probabilities, as presented in Section 6 below, perform the best. (The model specified in Column 5, which controls for the asset bubble and current account hypotheses of financial crises, is also a strong candidate model, though its out-of-sample performance is less robust.)

Figure 2 visualizes the positive and significant relationship between the interaction term and financial crises for the two most preferred models. The plot is a non-parametric visualization of the conditional expectation function produced by grouping the x-axis variable, the interaction term between wealth inequality and aggregate wealth, into equal-sized bins and then computing the mean of the x-axis and y-axis variables for each bin. The resulting scatterplot also controls for the same covariates included in the LPM models in Table 1.

5 Robustness Checks

This section presents findings on and discusses four robustness checks of the empirical results. First, a richer lag structure is applied to the control variables, allowing for greater dynamics.

Second, the data sample is restricted by excluding either countries that dominate the sample or the Global Financial Crisis. Third, the empirical relationship in Equation (1) is estimated with a fixed effects logit model. Finally, income inequality is substituted for wealth inequality to confirm that the distribution of stocks does in fact have more explanatory power than the distribution of flows.

5.1 Full lag structure

In the LPM estimated in the previous section, each variable entered the model in lagged first differences. However, some of the control variables, when regressed independently, show significance beyond the first lag. Therefore, a richer lag structure is estimated for some control variables based on a step-wise lag-order selection procedure whereby each control variable is independently regressed with the financial crisis indicator, and insignificant lag lengths are incrementally removed until the longest lag order is significant at one percent in the bivariate regression. As a result of this procedure, the housing price index variable now enters with a lag order of two, and both the real current account and broad money variables have lag orders of three. All other variables maintain the first lag, and all variables remain in first differences. Five of six the models with significant interaction terms in Table 1 remain robust and significant for the interaction variable under the full lag structure.

5.2 Country or data exclusions

Given the heavily unbalanced panel data utilized, the empirical results are tested by individually excluding those countries with the greatest number of observations: France, Great Britain, and the US. (Recall Figure 1 to see a visualization of observations by country.) In the sub-sample from the model specification in Column 2 of Table 1, for example, those three countries have 100, 99, and 101 observations, respectively. The countries with the next highest number are Denmark and Norway, both with only 29 observations. All seven of the models with the interaction term between wealth inequality and aggregate wealth retain positive and significant coefficients on the interaction variable when excluding France from the sample. However, the results are not robust to excluding either Great Britain or the US.

In another exclusion exercise, the models are all estimated for only the above three countries, which are also those whose wealth inequality measurements are derived using the capitalization method and national accounts data. The results are generally of similar sign and significance, with the exception of the models in Column 4 (controlling only for asset bubbles) and Column 6 (controlling only for broad money and credit growth). Perhaps more revealing is when the models are estimated excluding France, Great Britain and the US at once. The largest sample size shrinks to only 128 observations and none of the specifications remain significant. Furthermore, the models controlling for financial sector size, in Columns 3 and 8, become negative in the interaction term—though the number of observations is limited to only 81.

While the incidence of crises is somewhat sporadic, four of nine countries in the sample experienced a systemic crisis as part of the Global Financial Crisis (GFC). The LPM models are therefore re-estimated by excluding the GFC and ending the sample in 2006. The parameter in all seven models with the interaction term between wealth inequality and aggregate wealth remains significant and positive.

The final data exclusion is actually a substitution. Wealth inequality measurements using the capitalization method for the US are substituted with the estate-tax method measurements from Kopczuk & Saez (2004). The estate-tax data are shorter, ending in 2003, and diverge from the strong increase in wealth inequality observed in the capitalization method data (as well as household survey data). Much like the lack of robustness when omitting the US from the data sample, the empirical results on the interaction term are not robust to substituting the US wealth inequality data with an alternative to the capitalization measurement method.

5.3 Fixed effect logit

A conditional or 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

$$\Pr(crisis_{it}=1)=\left\{1+\exp\left[\beta_1\Delta top1nw_{it-1}+\beta_2\Delta\left(\frac{W}{Y}\right)_{it-1}+\beta_3\left(\Delta top1nw\times\Delta\frac{W}{Y}\right)_{it-1}\right.\right.$$
$$\left.\left.+\ \phi'\mathbf{\Delta X}_{it-1}+\alpha_i\right]\right\}^{-1}. \tag{2}$$

Results estimating the likelihood of financial crises are shown in Table C.4 of the online material. In each of the model specifications including the interaction term between wealth inequality and aggregate wealth (Column 2–8), the coefficient on the interaction variable is very positive and significant. Unlike the LPM results, several control variables become highly significant as well. For instance, broad money is very positive and significant in each model it enters. The short-term interest rate is also very positive and significant in both models it's included in, and real investment is negative and significant. Financial sector size, which was positive and significant in the LPM estimations, is no longer significant in the logit models. Note that in the logit estimations, Australia is dropped from each specification because all of its observations are negative outcomes and Denmark is dropped from the specifications in Columns 3, 5, 7, and 8 for the same reason.

5.4 Income inequality

Is the emphasis on wealth inequality rather than income inequality warranted? Or, does income inequality also relate to future unstable financial markets, as Malinen (2016) and Kirschenmann et al. (2016) find, and even Kiley (2018) finds despite his emphasis on current account deficits? To confirm the robustness of the wealth inequality results, 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. The income inequality data also come from the WID. Model specifications corresponding to Columns 2 and 4 in Table 1 are the only estimates with positive and significant coefficients on the interaction term between income inequality and aggregate wealth, though only at ten percent. However, the alternative specifications are inconsistent in both the sign and magnitude of the coefficient on the interaction term, and none are significant. A Davidson & MacKinnon (1981) J test of model specification confirms the lack of explanatory power for income inequality in each financial crisis model.[4]

In a final robustness check, simple partial regression plots are carried out to determine if any of the remaining variation from the original LPM estimates might be explained by income inequality. That is, the wealth inequality LPM models from Table 1 are estimated and their residuals are calculated. Then, the residuals are plotted against the lagged first difference of top income shares. If the plots reveal any non-random pattern, then income inequality should be tested as an explanatory variable more thoroughly. For each model the partial regression plot is horizontally clustered around the x-axis as horizontal lines and there is no indication of any relationship to income inequality.

These results collectively bolster the 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.

6 Predicting Crises

As previously noted, using the LPM to predict binary outcomes can be misguided as the estimated values—unlike in the logit model—are not bounded between zero and one. Though all the LPM models do predict negative probabilities, including the two most preferred specifications, their mean predicted probabilities of crisis are always positive, near zero, and the maximum predicted probabilities are always at least five standard deviations above the mean. Perhaps most importantly, as revealed below, their predictive performance for the three countries with the most data points available (France, Great Britain, and the US) is strong. This is especially evident when compared to the prevailing logit model of Schularick & Taylor (2012), henceforth S&T. For example, both Kiley (2018) and Kumhof et al. (2015) use it as a benchmark, the latter to estimate the level of endogenous financial instability created through inequality and leverage in their DSGE model.

The S&T benchmark model is

[4] Though problems exist in the estimation which increase the likelihood of over-rejection (i.e. a finite sample and a model under test with only moderate fit), one still fails to reject that the predicted income inequality model regressor is statistically different from zero.

$$\Pr(crisis_{it} = 1) = \left\{ 1 + \exp\left[\alpha_i + \sum_{k=1}^{5} \beta_k \Delta \ln rcredit_{it-k} \right] \right\}^{-1}, \tag{3}$$

where *rcredit* is the same real bank loans control variable included in the preferred LPM model specification (Column 7 of Table 1).

Predicted crisis probabilities are presented graphically in Figures 3–5. Vertical gray bars represent a financial crisis year, the solid blue lines represent the predicted crisis probabilities from the S&T benchmark model in Equation (3), and the dashed green lines represent the preferred LPM model's predictions. Both are within-sample predictions. In each plot the orange diamond represents the out-of-sample LPM forecast of the GFC's probability.[5]

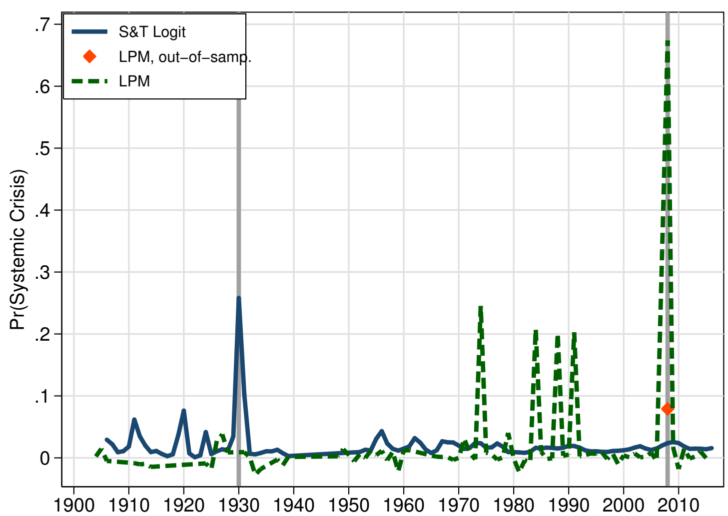


Figure 3: PREDICTED PROBABILITY OF FINANCIAL CRISIS: FRANCE

Beginning with the predicted crises for France in Figure 3, a few results stand out. First, the S&T model notably outperforms within-sample predictions of the 1930 financial crisis. Second, the preferred LPM model easily outperforms the S&T model in predicting the GFC, both in- and out-of-sample. (In fact, three of the seven specifications outperform the S&T model in out-of-sample forecasting the GFC.) Third, there are four false positives from the LPM predictions, in 1974, 1984, 1988 and 1991. Each roughly corresponds to a series of stock market crashes listed by Reinhart &

[5]Though predicted probabilities are only presented for the preferred model specification, each of the seven models including the interaction term of wealth inequality with aggregate wealth easily outperforms the S&T model in predicting financial crises for each of the three countries.

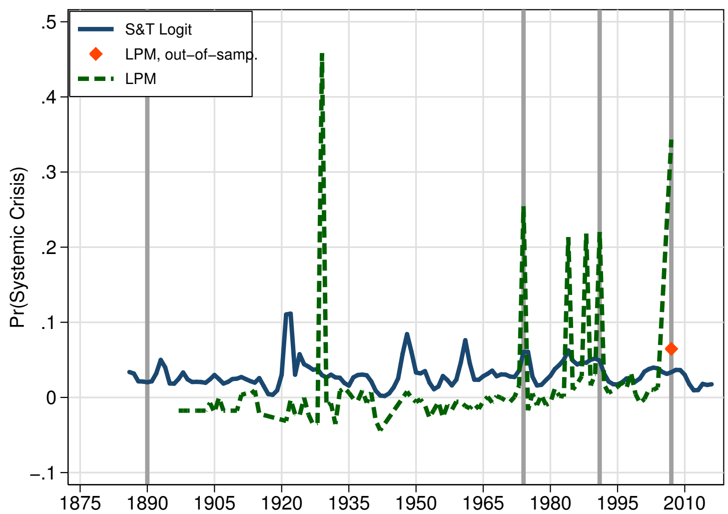


Figure 4: Predicted Probability of Financial Crisis: Great Britain

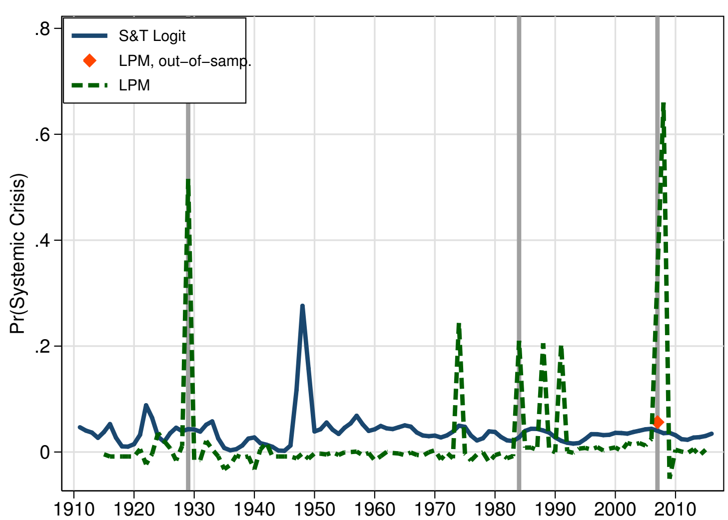


Figure 5: Predicted Probability of Financial Crisis: United States

Rogoff (2010).

The predictions for Great Britain by the LPM model in Figure 4, while strongly more predictive of financial crises in 1974, 1991, and 2007 than the S&T model, also generate a serious warning in 1929. No systemic financial crisis is catalogued by Jorda et al. (2017) for that year, but Reinhart & Rogoff do document an onset of three consecutive years of stock market crashes wherein the third year (in 1931) also included a currency crisis. The model therefore appears sensitive to financial instability that may not necessarily be diagnosed ex-post as a systemic crisis. Also, the LPM model's out-of-sample forecast of the GFC indicates a greater probability than the within-sample forecast of the S&T model for Great Britain.

Financial crisis predictions for the US in Figure 5 share many of the same characteristics that the French and British cases do: strong within-sample forecasting, superior out-of-sample forecasting of the GFC, and numerous false positives that indicate underlying financial instability—though not ultimately deemed a systemic crisis. The crisis predictions in non-crisis years of 1974, 1988, and 1991 correspond to a stock market crash, banking crisis, and then both together in 1991, according to Reinhart & Rogoff.

The strong predictive performance of the preferred LPM model, as well as other specifications, extends beyond the scope of the three countries discussed above. For example, the preferred LPM model predicts the GFC well for Sweden, though its data sample only begins in 2000, and also Spain. In the case of Denmark, its systemic crisis in 1921 is very well predicted as that is the only crisis event in its history that also includes sufficient surrounding data observations. And for Norway the LPM model does not predict the 1988 crisis as data only begin five years prior, but it does predict a significant likelihood of crisis in 2008 despite the fact that a systemic crisis was not determined for the country in Jorda et al. (2017), even though it experienced both a currency crisis as well as a stock market crash, as listed in Reinhart & Rogoff. Hence, the LPM models reveal financial instability even when the determined crisis outcome is debatable.

Overall, the empirical model's predicted crisis results are consistent enough to lend support to the consistent finding that wealth inequality, in sufficiently wealthy economies, plays a unique role in financial stability, one that income inequality does not, and cannot, capture. However, given that the empirical results are strongly dependent on British and American financial histories and data, more data are needed to help defend this conclusion beyond the Anglo-Saxon paradigm.

7 Discussion

This section discusses two interpretations of the empirical findings presented above. The central question is, why might the interaction of wealth inequality with aggregate wealth have a positive relationship with future financial crises?

The first interpretation, detailed in Hauner (2017), posits that an economy's arrangement of financial links, conditional on the number of links, is related to the stability of that economy when shocked. Consider a closed network of individuals whose aggregate wealth, as a collection financial assets, by definition creates financial links in the network between creditors and debtors. The model assumes one type of financial asset exists, an individual's claim on some future cash flow that is generated by another individual's labor income. Specifically, the total number of financial assets an individual owns represents their *in-degree* and the distribution of assets in the network economy is described by an *in-degree distribution*. This is equivalent to the wealth distribution since it is assumed that the non-financial assets that generate labor income are homogeneous. As the distribution of wealth changes the distribution of links in the network also changes. The same is true when aggregate wealth changes and so both alter the topology of links in the interpersonal financial network.

Though the network in this model is static, with no individual optimization problems, contagion is a dynamic process, where the level of contagion is equivalent to instability. Contagion occurs when a random negative income shock (think of the loss of a job or earning capacity) causes an individual's net worth, the sum of their financial and non-financial assets minus liabilities, to drop below some relative threshold and causes them to fail financially. Such a failure has associated costs. Those costs wipe out collateral wealth for the now failing individual because an individual's net worth is assumed to collateralize their financial liabilities, much like an asset-backed security. The network structure implies one individual's net worth is linked to, and dependent upon, the net worth of others. Therefore decreases in net worth from the initial shock spread from one individual to another until some steady state is reached. The share of the network that has failed financially is the model's measure of instability. Network simulations in Hauner (2017), in which the arrangement of financial links is random but the level of wealth and inequality is imposed, demonstrate that the model economies are more unstable when they both exhibit high wealth inequality and are sufficiently wealthy in aggregate.

The above network model embeds several features of Hyman Minsky's Financial Instability Hypothesis, a common framework for interpreting financial crises but which has no explicit role for wealth distributions.[6] First, individual balance sheets are interrelated, where one's asset is always another's liability. Second, assets and liabilities represent commitments to future cash flows, where the flows across network links are what Minsky called a "complex system of money in/money out transactions."[7] Third, a collapse in asset values stifles future cash flows and catalyzes a crisis, or as Kregel (2014) argues, only a "slight disturbance" in money flows is necessary to cause instability and "widespread financial distress." And lastly, a growing financial economy increases the scale of contagion.

Alternatively, a less technical, higher-level, and perhaps more intuitive interpretation of the empirical results can be summarized by the derivation of the interaction term between wealth inequality and aggregate wealth. In levels, the interaction term simplifies to $top1wealth/Y$ after cross-multiplying, or the ratio between nominal net wealth held by the top 1% and aggregate income. The empirical results may then describe the importance of the proportion of the wealth held by the top relative to total income, or, when reinterpreted through the network model lens of creditors and debtors, the flows available to borrowers to service the assets of top wealth holders. This ratio can grow, but not indefinitely. The economy will reach a point of collapse when debts can no longer be paid and a crisis ensues. This is an acknowledgement of the underlying risk to every economy that debts may grow beyond the ability of debtors to pay. In this interpretation, the wealth inequality-aggregate wealth interaction term may simply be serving as a barometer of that risk. When financial pressures peak, their release manifests in a systemic crisis.

[6] While not an explicit network model, Minsky's framework generates endogenous instability in a financial economy of connected banks and firms rather than individuals. See Minsky (1975) and Minsky (1986a) for longer expositions, or Minsky (1992) for a brief summary.

[7] See (Minsky, 1986b, p. 69).

Of course the economic polarization this ratio measures is not inevitably increasing but rather a political choice. In ancient Mesopotamia, this tendency towards polarization and unconstrained wealth and debt was reversed through cyclical debt jubilees issued by kings, as detailed by Hudson (1993) and Graeber (2011). In more recent times, high marginal tax rates of up to 91 percent were imposed on the wealthiest households to counteract this tendency.

8 Conclusion

This paper finds strong empirical evidence of a positive relationship between wealth inequality, aggregate wealth and the likelihood of a financial crisis. Using panel data from nine countries (Australia, Denmark, France, Great Britain, the Netherlands, Norway, Spain, Sweden, and the US) with historic data beginning in 1870, and testing the relationship with a two-way fixed effects linear probability model, the finding is robust to the estimation method and numerous controls, namely bank credit, broad money, and stock and housing bubbles. The positive relationship is also robust to excluding the Global Financial Crisis from the data sample and estimation method. The consistent predictive performance of the linear probability model, despite not being bounded between zero and one, gives further support to the empirical finding, particularly when compared to a leading benchmark model based only on country fixed effects and credit growth. That income inequality is not found to have a statistically significant role in this relationship lends more credence to the argument put forth that there is a unique role for the stock of financial assets and its distribution in determining financial crises.

What might that role be? Keynes once described the relationship between debtors and creditors as forming "the ultimate foundation of capitalism." So one possible role is that the interaction between wealth inequality with aggregate wealth is a measure of how strained this foundational relationship is. When debtors can no longer pay they don't, and the financial wealth those cash flows sustain collapses along with the economy in a systemic crisis.

An alternative role, one explored at length in Hauner (2017), is that the wealth inequality and aggregate wealth of an economy describe the topology of financial linkages between creditors and debtors in an economy. The distribution of wealth describes the skewness of financial links in a networked financial economy and aggregate wealth describes the total number of links. Together they are key determinants of the economy's robustness in the event of a shock. For example, 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 in Hauner (2017) show. This interpretation echoes much of the intuition from the banking network contagion literature.

One implication of this paper's empirical findings is that future increases in wealth inequality (as predicted by Piketty) in the US and other financially advanced economies will 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 concentration, 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.

Data limitations motivate continued study to understand these relationships more precisely. While annual top wealth share estimates exist for the United States, France and Great Britain—and the empirical results are most robust for those three countries—there is still a paucity of annual wealth inequality data for most other developed economies let alone developing ones. As the survey by 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.

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