WEALTH INEQUALITY, ASSET PRICE BUBBLES AND FINANCIAL CRISES

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Abstract

This paper examines the role of wealth inequality as a predictor of financial crises, analyzing data from 18 countries between 1870 and 2020. Unlike previous research focused on the effects of financial crises on inequality, we explore whether increases in wealth concentration—specifically in the top 1%—elevate crisis risk. Our findings indicate that, even after accounting for key crisis predictors, a one standard deviation rise in the growth of the top 1% wealth share is associated with a 3 to 8 percentage points increase in crisis probability, with results robust across various crisis lists and empirical approaches. Temporal dynamics reveal that while a credit boom can jeopardize the financial system as early as the following year, it takes several years for an increase in private wealth accumulation and wealth concentration at the top to significantly heighten the risk of a systemic bank run, serving as early signals of potential instability. Furthermore, we find evidence that asset price bubbles can serve as transmission channels, although these relationships vary by asset class and "bubble" definition. Our findings suggest that addressing wealth concentration could reduce inequality while acting as a stabilizing force for financial systems, highlighting the importance of incorporating broader inequality metrics in crisis prediction models and exploring policy mechanisms to mitigate systemic risks.

JEL Classification: D31, G01, G17, N10

Keywords: Wealth inequality, Wealth concentration, Private wealth-income ratio, Asset price bubbles, Financial crises

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1 Introduction

The aftermath of the 2008 Great Financial Crisis (GFC) has intensified research interest in both the consequences and, arguably more critically, the causes of financial crises. While some view financial crises as exogenous shocks occurring independently of economic disequilibrium, a growing body of literature highlights their recurrent nature, implying a structural predictability. Sufi and Taylor (2022) provide a comprehensive survey of this literature, emphasizing the predictive role of credit expansion and asset price growth in financial crises.

In this paper, we examine the inequality-crisis nexus. Several empirical studies investigate how financial crises impact economic inequality, whereas our interest lies in the reverse relationship: inequality as a potential predictor of financial crises.[1] Although some research explores the role of income in this regard, the influence of wealth has received relatively little attention. We aim to fill this gap by answering the question: does wealth inequality affect the likelihood of financial crises?

Our research is motivated by two hypotheses that connect inequality to financial crises. First, the "Rajan hypothesis," articulated by Rajan (2010), posits that stagnating real incomes of low- and middle-income households prior to the GFC prompted policymakers to deregulate the financial sector in order to soothe discontent. This deregulation allowed these households to temporarily sustain consumption and employment while accumulating higher debt levels, ultimately resulting in the credit bubble that collapsed in 2008. Second, because wealth accumulation can be explained by an increase in savings (volume effect) or asset prices (relative price effect), Piketty and Zucman (2014) argue that the wealth-income ratio can act as an early indicator of asset price bubbles. This is evidenced by the rapid wealth accumulation observed in Japan during the 1980s and Spain in the 2000s, which preceded economic downturns triggered by the bursting of these bubbles.

[1] These studies focus mainly on income inequality. For a summary of how financial and other crises affect income inequality, see Bodea et al. (2021). Rare exceptions examining wealth inequality include Shchepeleva et al. (2022) and Ovcharenko (2024). In contrast, Pfeffer et al. (2013) and McKernan et al. (2014) use microdata to analyze wealth disparities in the aftermath of the GFC.

Why does wealth inequality matter more than income inequality and what are the channels through which it could trigger a financial crisis? Contemporary research, exemplified by Piketty (2014) and furthered by studies like Chancel et al. (2022), shows that wealth is significantly more concentrated than income, a disparity that intensifies income inequality through two main mechanisms: the generation of capital income and intergenerational transfers. The role of wealth in shaping economic inequality is both self-reinforcing and systemic. As wealth accumulation consistently yields capital income (such as profits, interests, rents, dividends, etc.), it perpetuates inequalities through inheritance, leading to persistently skewed distributions.

This wealth concentration interacts directly with the dynamics of financial crises due to the composition of wealth in real and financial assets, both of which are linked to key crisis indicators such as asset price growth and credit expansion. For example, housing and other real assets often serve as collateral in credit markets, while financial assets, such as savings, bolster bank liquidity and stimulate lending, creating systemic vulnerabilities (Kumhof et al., 2015; Mian et al., 2020). Furthermore, factors such as less risk-averse behavior or more optimistic expectations of future returns among the wealthiest are important drivers of asset prices (Toda and Walsh, 2020; Gomez et al., 2024). Consequently, asset price inflation driven by wealth concentration, particularly in the equity or housing markets, becomes a crucial channel for crisis formation (Bryant and Süssmuth, 2019).

For our analysis, we integrate data on wealth inequality and private wealth accumulation with historical macro-financial indicators from 18 countries spanning from 1870 to 2020. Taking into account other significant predictors of financial crises identified in the literature, we first investigate the role of increasing wealth concentration on the likelihood of financial crises. Subsequently, we evaluate whether asset price bubbles act as a viable transmission channel for this relationship. To ensure the robustness of the main findings, we conduct various checks by adopting alternative definitions of credit and chronologies of crises. Further, we restrict the sample to different time periods, and employ additional empirical strategies.

Our main finding is that increasing wealth inequality is associated with a higher probability of financial crises, even after controlling for key predictors. This relationship holds across different crises chronologies, credit definitions, time periods, and empirical strategies. Specifically, a one standard deviation increase in the growth of the top 1% wealth share is associated with a 3 to 8 percentage points (pp) increase in the probability of financial crises, with all results statistically significant at the 1% level. Furthermore, given the lag structure of our models, our results indicate that the likelihood of a financial crisis exhibits different temporal dynamics with respect to credit expansion, growth in the private wealth-income ratio, and growth in wealth concentration. While a credit boom can jeopardize the financial system as early as the following year, it takes a couple of years for a higher concentration of wealth at the top percentile and three or four years for a rise in private wealth accumulation to significantly raise the risk of a systemic bank run.

In exploring transmission channels, we provide empirical support for the hypothesis put forward by Piketty and Zucman (2014). Our findings show that the growth in the private wealth-income ratio and the share of wealth held by the top 1% are positively correlated with the likelihood of house and equity price bubbles. However, these relationships come with important caveats regarding bubble definitions and sample sizes. These caveats emphasize the importance of methodological rigor in evaluating the relationship between wealth inequality and asset price bubbles.

The remainder of this paper is structured as follows. Section 2 reviews the literature on the inequality-crisis nexus. Section 3 details the data and definitions used in this paper. Section 4 describes the empirical methods used for the main analysis and subsequent robustness checks. Section 5 presents the results. Section 6 interprets these findings in the context of the inequality-crisis literature. Section 7 summarizes the main findings and proposes avenues for future research.

2 Literature review

2.1 Income inequality and financial crises

Major economic recessions as consequences of financial crises have spurred a large body of research on the causes of such events. Economists in particular have been interested in understanding the factors that may help predict these crises. Through a thorough review of this literature, Sufi and Taylor (2022) emphasize credit expansion and asset price growth as key predictors of financial crises. They trace these findings from the early influential works by Kindleberger (1978) and Minsky (1986), to more contemporary empirical contributions by Ivaschenko (2002), Schularick and Taylor (2012), Jordà et al. (2015b), Richter et al. (2021), and Greenwood et al. (2022).

Although these two remain key factors, the pool of predictors as shown by Sufi and Taylor (2022) is larger. The quest for understanding the causes of the GFC has led several renowned economists to highlight a less obvious factor: economic inequality. Such a proposition, which stemmed from Rajan (2010) and is often referred to as the "Rajan hypothesis", claims that the real incomes of low- and middle- income households have stagnated in periods preceding the episodes of financial crises. To soothe any discontent, the argument goes, politicians have allowed for more deregulation of the financial sector, which allowed low- and medium-income households to maintain consumption and employment for while. In the process, these accumulated debts built up into a credit bubble, which eventually burst.

While agreeing with the "Rajan hypothesis" on the role that politics played in financial deregulation, Acemoglu (2011) disagrees with the direct causal relationship between inequality and financial crises. Instead, he suggests that the political response through financial deregulation led to both rising income concentration at the top and circumstances that caused the GFC. Despite these debates on the mechanisms, other economists, such as Joseph Stiglitz and Robert Reich, argue along similar lines to Rajan (2010) (see Stiglitz, 2012; Reich, 2013). In fact, even before them, Galbraith (1954) emphasized the "bad distribution of income" as one of the main factors that contributed to the Great Crash of 1929, which precipitated the subsequent Great Depression. Van Treeck (2014) and Perugini et al. (2016) provide detailed reviews of the literature on the inequality-crisis nexus.

Several studies have empirically tested the relationship between income inequality, credit growth, and crisis. Atkinson and Morelli (2010) provide an early summary on the topic and Atkinson and Morelli (2011) conduct a descriptive analysis using data from 25 countries during the period 1911-2010, but their inconclusive results pave the way for further investigation. Using a richer dataset, Morelli and Atkinson (2015) revisit this issue by reassessing their earlier empirical evidence on whether the growing level of inequality, which they refer to as the "growth" hypothesis or the high levels of inequality, which they refer to as the "level" hypothesis, predicts financial crises. Again, they find no conclusive evidence to support either of them.

Other empirical studies could be classified into two broad categories according to the type of relationship they investigate. Some studies test the direct relationship by regressing a variable that quantifies financial crises on income inequality, usually through linear probability or logit models. Because works such as Schularick and Taylor (2012) provide robust evidence on the role that credit growth plays in the likelihood of crises, other studies try to establish a relationship between income inequality and financial crises by using credit growth as a transmission channel. Thus, they regress credit growth, rather than financial crises, on income inequality. For example, using data from 14 developed economies from 1920 to 2008, Bordo and Meissner (2012) employ ordinary least squares regressions to find only statistically insignificant relationships between income inequality and credit growth.

In contrast, Isojärvi and Jerow (2024) assess the relationship between economic inequality and numerous indicators from four categories of the *Financial Stability Report* of the Federal Reserve Board: nonfinancial leverage, asset valuations, financial leverage, and funding risk. In addition to confirming the role of the increasing income inequality in household leverage and equity valuation relative to GDP, they find that an increase in income inequality is associated with an increase in additional vulnerability indicators such as corporate bond debt relative to GDP, the ratio of assets to GDP, mutual funds and life insurers, and the non-bank short-term wholesale funding, in the financial system of the United States (US).

Klein (2015) and Malinen (2016), on the other hand, use panel cointegration techniques to find that there is a positive and significant relationship between income inequality and credit. Perugini et al. (2016) apply various econometric techniques to panel data covering 18 OECD countries from 1970 to 2007 and reach the same conclusion. Using long panel data from a century covering 10 developed economies, Destek and Koksel (2019) employ a bootstrap rolling-window estimation procedure to find that increasing income inequality has a positive predictive power on credit booms in Anglo-Saxon but not in Scandinavian and continental European countries.

The literature on the direct relationship between growing income inequality and financial crises is rather nascent. Kirschenmann et al. (2016) employ logit models on data from 14 countries covering the period 1870 to 2008 to find a positive relationship between income inequality and financial crises. These findings are also confirmed by Paul (2023), who analyze both the increasing top income inequality and low productivity growth in the run-up to crises. However, neither study examines the role of wealth inequality.

2.2 Empirical gaps in understanding the role of wealth

Both the hypotheses and the empirical work on the inequality-crisis nexus have focused primarily on the role of the distribution of income. Probably due to unavailability of reliable wealth data, the distribution of wealth has been mostly implied or neglected. However, there are two main economic reasons why wealth inequality conveys even more important information than income inequality. The first is because of its deterministic power on income inequality, and the second is because of its relationship to the main predictors of financial crises recognized in this strand of literature—namely, credit expansion and asset price growth.

First, as shown by Piketty (2014) and subsequent studies, such as Chancel et al. (2022), wealth is more concentrated than income, and this inequality determines the dynamics between the two. Wealth has two key characteristics that make it a major determinant of income inequality: (i) it generates capital income (e.g., profits, interests, rents, dividends, capital gains) over the life cycle, which is the primary source of income for high-income earners, and (ii) it can be transferred across generations as inheritance, reinforcing wealth and income inequality over time.[2] To emphasize the deterministic role of wealth distribution, Piketty (2014) argues that the decline in overall income inequality during the first half of the twentieth century was largely due to a reduction in capital income, which stemmed from a decrease in wealth inequality.

Second, the accounting definition of wealth is closely related to the main predictors of financial crises. Wealth comprises both real and financial assets and is influenced by liabilities, all of which are directly connected to factors that signal potential crises. For example, real assets such as housing or other real estate can be leveraged as collateral for loans, while financial assets, such as savings, can enhance the liquidity of banks and stimulate credit expansion. Kumhof et al. (2015) introduce a dynamic stochastic general equilibrium model in which the financial wealth of the top 5% of the income distribution enables debt-financed consumption by the bottom 95%. This increases the debt-to-income ratio of the latter, which can risk financial stability and make a systemic crisis more likely. Mian et al. (2020) refer to this as the "saving glut of the rich," where the rise in the financial wealth of the top 1% in the US has not led to more investment in the real economy, but rather enabled dissaving by the bottom 90% and the government.

Moreover, the price growth of specific financial assets, such as equity, or real assets, such as housing, is another channel through which crises can be triggered. Bryant and Süssmuth (2019) provide empirical evidence for the co-movement of wealth concentration and asset prices in the US and the United Kingdom (UK). They find that wealth concentration is pos-

[2] While income also affects wealth accumulation through savings, a central conclusion of Piketty (2014) is that historically, the rate of return on capital (r) has exceeded the economic growth rate (g) (i.e., $r > g$), leading to a faster growth of wealth than income.

itively associated with stock prices in both countries, but the relationship with house prices holds only in the US. In contrast, these relationships are not observed in France, possibly due to institutional differences such as varying tax rates on capital gains and redistribution policies (Bryant and Süssmuth, 2019, p. 337).

In elaborating the transmission channels, Toda and Walsh (2020) argue that as wealth concentrates, demand for high-risk assets increases, amplifying the volatility of asset prices. In an economy with heterogeneous risk preferences and return expectations, wealth shifts toward optimistic or less risk-averse investors increase demand for risky assets, raising prices and lowering risk premiums to reach market equilibrium (Toda and Walsh, 2020, p. 3584). Their intuition is motivated by Fisher (1910), who emphasizes how the attitudes (e.g., less risk-averse) and beliefs (e.g., optimistic about future dividends) of the "enterpriser-borrower" can result in asset price fluctuations and eventually crisis (pp. 174-175). Such dynamics are further evidenced by Gomez et al. (2024), who describe the relationship as a "feedback loop". A positive shock in financial markets disproportionately benefits wealthier investors, increasing wealth concentration and driving up demand for riskier assets, thereby reinforcing the cycle between wealth inequality and asset price bubbles (Gomez et al., 2024, p. 3). Knüpfer et al. (2024) find that Norwegian households in the top 1% of the wealth distribution own approximately 80% of household-held stocks and account for around 70% of the household-attributable stock price volatility.

To our knowledge, the direct role of wealth inequality in financial crises has been empirically examined only once. Using panel data from nine countries, Hauner (2020) employs a two-way fixed effects linear probability model to estimate the relationship between the share of wealth held by the top 1% and national wealth-income ratios in financial crises. He finds that only the interaction of these two factors is positive and statistically significant, concluding that for wealth inequality to play a key role in financial stability, the economy must be sufficiently wealthy.

To fill this gap in the literature, we study the role of wealth inequality in the probability of financial crises with some pronounced differences from Hauner (2020). In summary, we use consistent data on wealth inequality, focus on private instead of national wealth-income ratio, employ other empirical strategies, and test potential channels. Thus, we present new and different results. As such, our work speaks to three strands of literature.

First, we contribute to the literature on the inequality-crisis nexus by providing new empirical evidence on the role of wealth rather than income inequality. Contrary to the finding of Hauner (2020), we find that being sufficiently wealthy is not a condition for the growing wealth inequality to play a role in the financial stability of an economy. Second, our work contributes to the literature on the determinants of financial crises by providing evidence on the role that the private wealth-income ratio plays in the likelihood of crises. It does so without interacting with wealth inequality, indicating that when wealth is growing faster than income in a society, which can be due to a higher volume (e.g., savings) or asset prices, this can have important implications for the financial stability of the economy. Third, to our knowledge, we provide the first empirical evidence on the role of wealth inequality and the private wealth-income ratio on the likelihood of asset price bubbles.[3] We show that when private wealth grows faster than national income and wealth concentrates more in the top percentile of the distribution, the probability of house and equity price bubbles increases. This suggests that asset price bubbles can serve as a transmission channel through which rising wealth concentration and the faster growth of private wealth relative to national income contribute to financial instability.

[3] A few papers focusing on individual or small groups of countries analyze related aspects but not bubbles specifically. For example, Bryant and Süssmuth (2019) find a positive relationship between wealth concentration and stock prices in the US and the UK, but not in France. Similarly, Isojärvi and Jerow (2024) find no statistically significant relationship between wealth inequality and equity premium in the US, but observe a positive and significant relationship with equity valuations at the 10% significance level.

3 Data

3.1 Main variables

The data used in this analysis come from two main sources. Wealth-related data, specifically the private wealth-income ratio and the share of wealth held by the top 1%, are sourced from the World Inequality Database (WID) (Alvaredo et al., 2020). These data are merged with the Jordà-Schularick-Taylor Macrohistory Database (Jordà et al., 2017), supplemented by bank balance sheet ratios from Jordà et al. (2021). This dataset includes historical macro-financial data for 18 developed countries—Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States—from 1870 to 2020.

The dependent variable in our main analysis is a dummy for financial crisis in the Macrohistory Database, which takes the value 1 to mark the first year of a financial crisis event and 0 otherwise. Schularick and Taylor (2012) define financial crises 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" (p. 1038). While this largely narrative-based approach to defining a crisis is widely used, Baron et al. (2021) criticize it for lacking the rigor of quantitative criteria. To address this limitation, we include additional sources in the robustness check section to ensure greater analytical precision.

As widely established in the literature, such as in the work of Schularick and Taylor (2012), credit growth is one of the most significant predictors of financial crises. To assess whether wealth inequality still plays a role, we control for credit growth in our analysis. Following Schularick and Taylor (2012), we define credit as total loans to the non-financial private sector, and, consistent with their approach, we adjust for inflation using the Consumer Price Index (CPI) to express credit in real terms. As a robustness check, we also employ an alternative definition commonly used in the literature, where credit is measured as the ratio of these loans to GDP, i.e., the loans-to-GDP ratio (Sufi and Taylor, 2022).

Our main independent variable is wealth inequality, measured as the share of wealth held by the top 1%.[4] While wealth concentration is an important indicator, Piketty (2014) and Piketty and Zucman (2014) also use the ratio of wealth to national income to highlight the importance of wealth in a society. A rising wealth-income ratio indicates an increasing importance of wealth relative to income, and given that wealth is more concentrated than income, it can also indicate a rise in overall inequality.

Moreover, Piketty and Zucman (2014) show that this wealth accumulation can come from savings (volume effect) or from a rise in asset prices (relative price effect). They emphasize peaks of the wealth-income ratio in Japan during the 1980s and Spain in the 2000s, both of which preceded financial crises, suggesting that this might signal the presence of an asset price bubble. Hauner (2020) also incorporates the national wealth-to-income ratio in his model.

However, national wealth in the WID is composed of both private and public wealth. In addition to the obvious disparities in the ownership, which imply different dynamics for inequality, Chancel et al. (2022) show that at least in the past four decades they have had diverging trends. While private wealth has grown, public wealth has shrunk. Thus, we focus on the growth of private wealth-income ratio as a measure of private wealth accumulation, as it is more important for the power relations which can influence policies that affect the financial stability of a country.[5]

Figure 1 shows trends in the loans-to-GDP ratio, private wealth-income ratio, and the top 1% wealth share across the 18 countries in our sample. The time periods vary by country, depending on the availability of data for all three variables. For instance, data from France, the Netherlands, the UK, and the US allow us to cover the entire 20$^{\text{th}}$ century up to 2020.

[4]Wealth is defined as personal net wealth (total assets minus liabilities), measured at the individual level of the adult population (over 20), with assets equally split within couples. For a detailed methodology and definition, see Alvaredo et al. (2020).

[5]Following the methodology of Alvaredo et al. (2020), private wealth-income ratio is defined as the market value of private net wealth relative to the market value of net national income.

In the cases of Denmark, Spain, and Switzerland, we have data spanning over approximately four decades. For the remaining countries, data points begin in 1995, offering more limited historical coverage.[6]

The number of crisis episodes, indicated by the shaded areas in Figure 1, is constrained by the availability of data for all three variables in each country. For example, although we have complete data from 1995 to 2020, the Macrohistorical Database reports no financial crises in Australia, Canada, Finland, or Norway during this period. In contrast, both the UK and the US have three crisis episodes, marking the highest number of financial crises per country. For the remaining countries, at least one episode is included, with the GFC being the most frequently observed across the sample.

Comparing these variables reveals two main trends. First, the movement of the private wealth-income ratio closely mirrors that of the loans-to-GDP ratio. Similar to credit expansion preceding a financial crisis, there is a rise in private wealth relative to national income in several instances. For example, before the GFC, this pattern is observed in Belgium, Denmark, France, Ireland, Italy, Portugal, Spain, Sweden, the UK, and the US. This trend is also evident in other episodes, such as the prelude to the Great Crash of 1929 in France and the US, as well as the early 1990s financial crisis in the UK.

Second, while the dynamic movement of the top 1% wealth share does not consistently mirror that of the loans-to-GDP ratio, there are several instances where either a general upward trend or a sharp increase precedes a financial crisis. This pattern is evident in Denmark, Germany, Italy, Spain, Sweden, Switzerland, and the US before the GFC. Similarly, before the financial crisis triggered by the Great Crash of 1929, sharp increases in the top 1% wealth share are observed in both France and the US. In the five years leading up to the crisis, the wealth share of the top 1% in France rose by approximately 5 pp, while in the US it increased by around 10 pp. These descriptive patterns further motivate our analysis to explore the role of wealth inequality in the likelihood of financial crises.

[6] Except for Germany, where the earliest data point is from 1993.

Figure 1: Credit, wealth concentration and financial crises

((a)) Loans/GDP ((b)) Wealth/Income ((c)) Top 1%

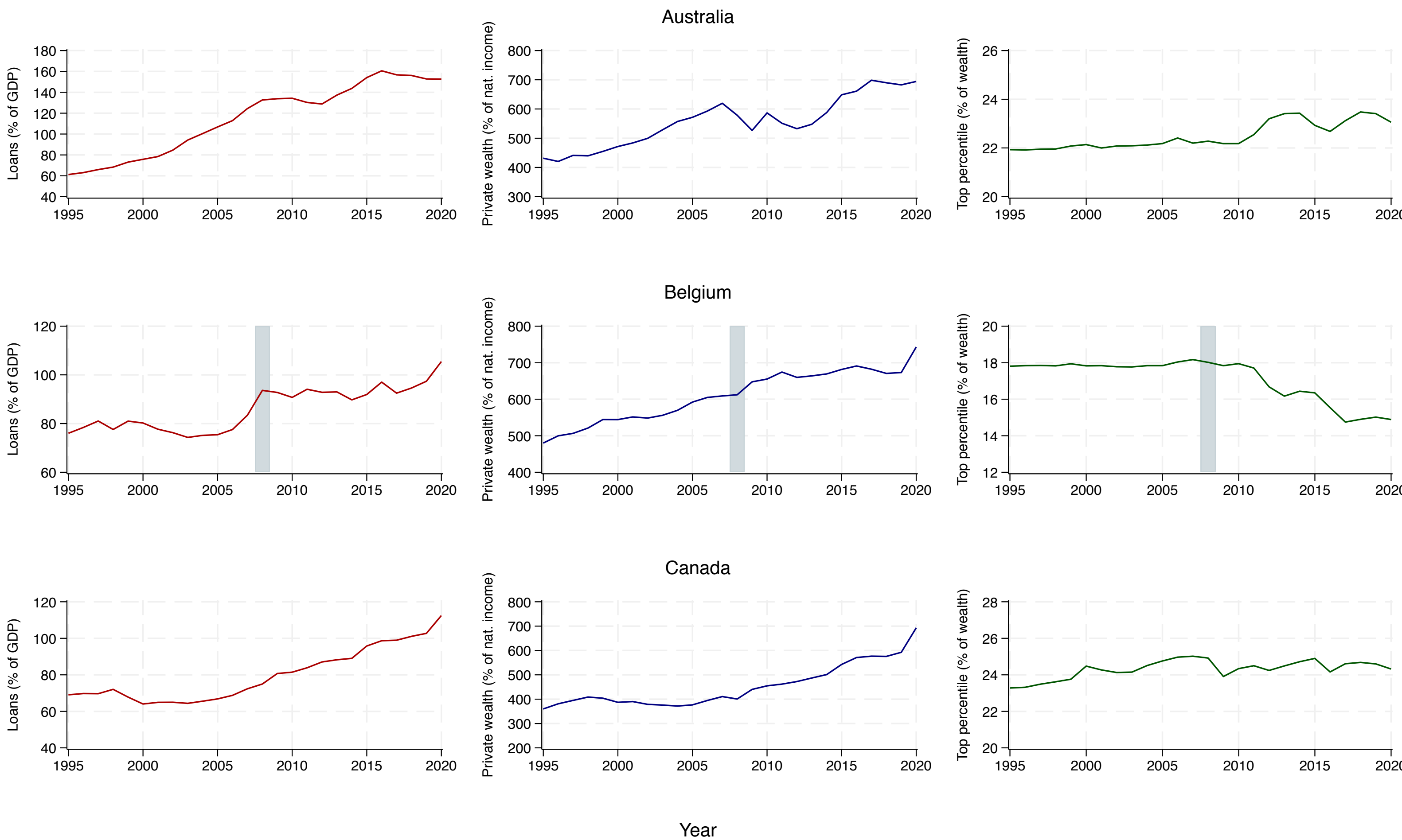


Figure 1: Credit, wealth concentration and financial crises (continued)

(a) Loans/GDP ((b)) Wealth/Income ((c)) Top 1%

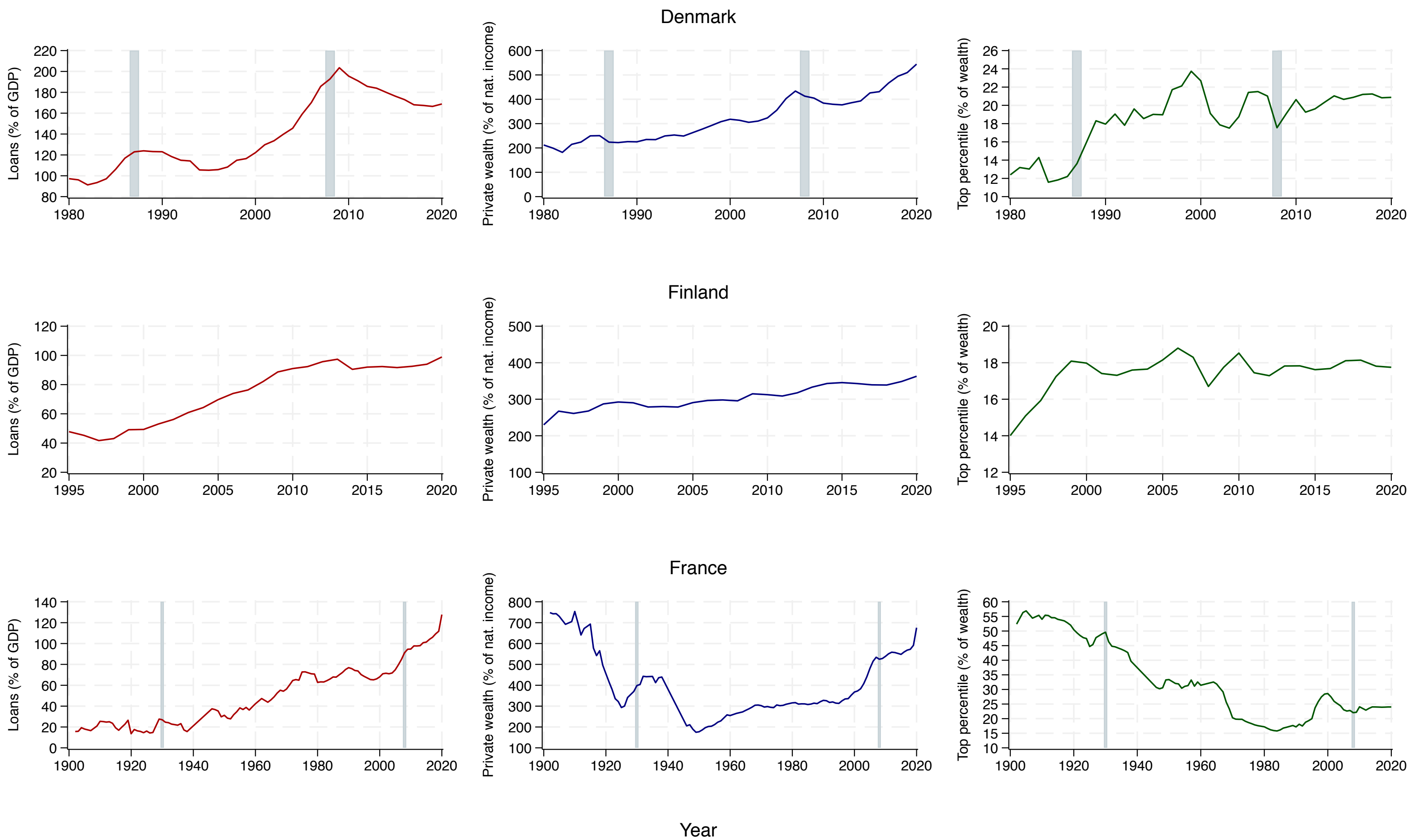


Figure 1: Credit, wealth concentration and financial crises (continued)

(a) Loans/GDP ((b)) Wealth/Income ((c)) Top 1%

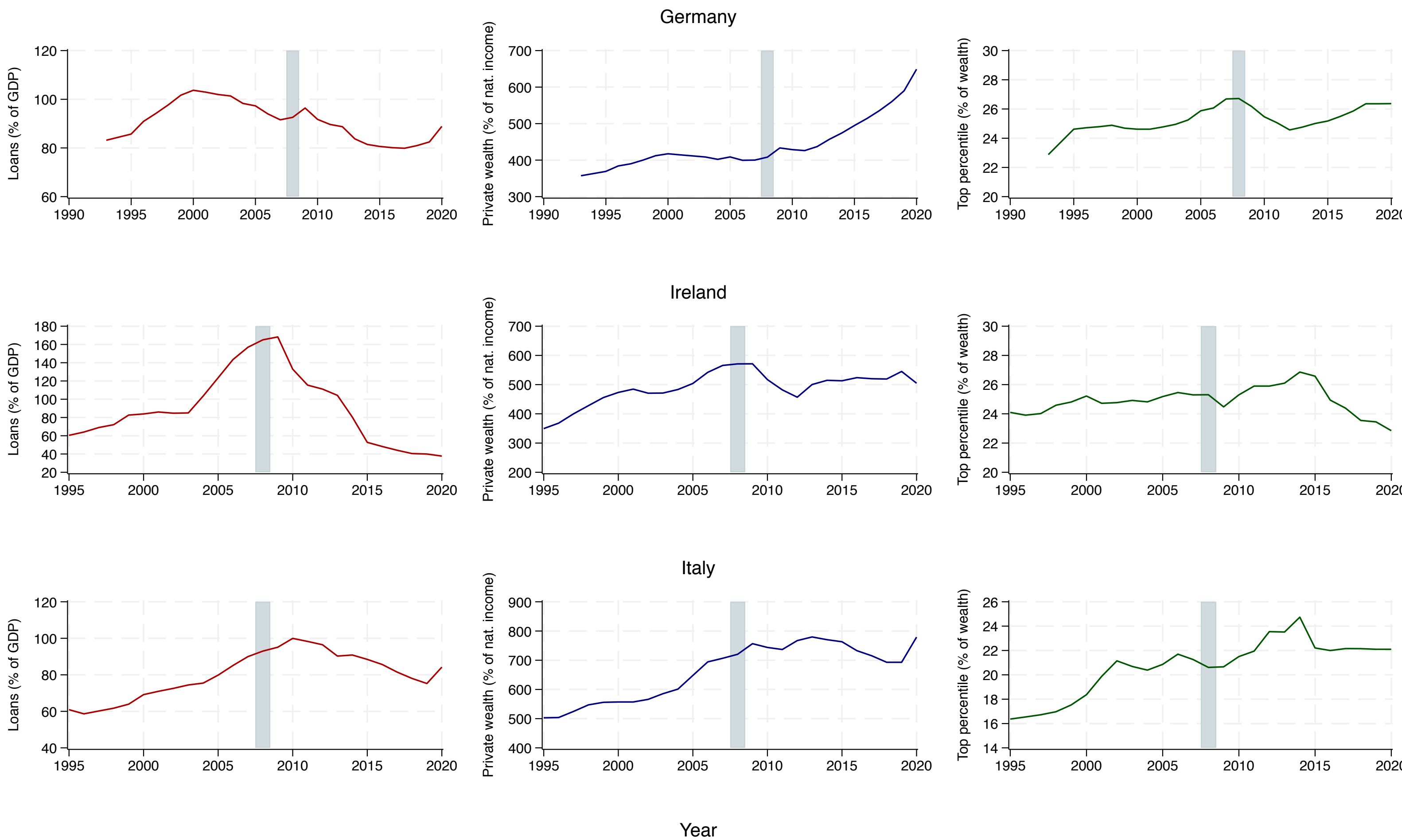


Figure 1: Credit, wealth concentration and financial crises (continued)

(a) Loans/GDP ((b)) Wealth/Income ((c)) Top 1% wealth share

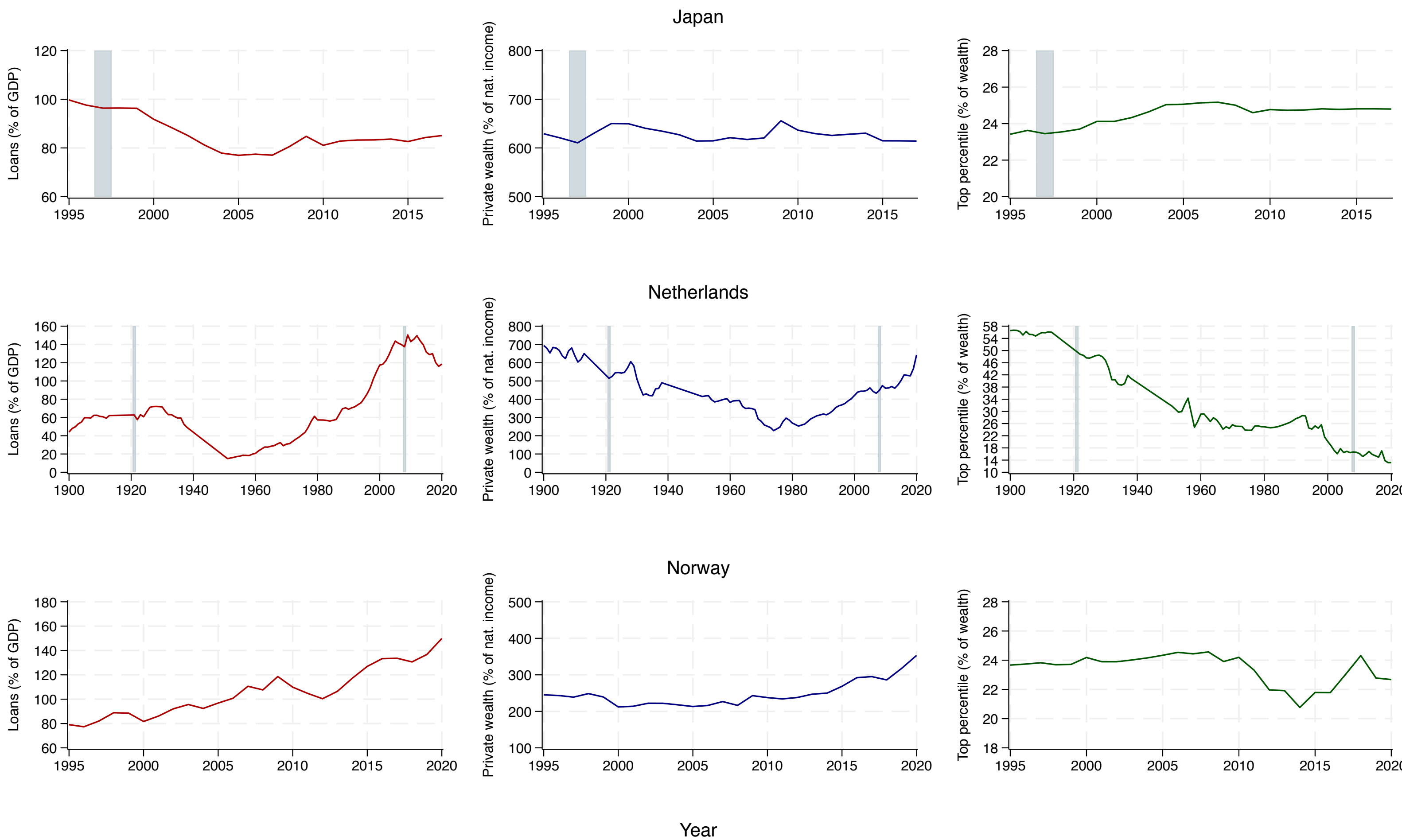


Figure 1: Credit, wealth concentration and financial crises (continued)

(a) Loans/GDP ((b)) Wealth/Income ((c)) Top 1%

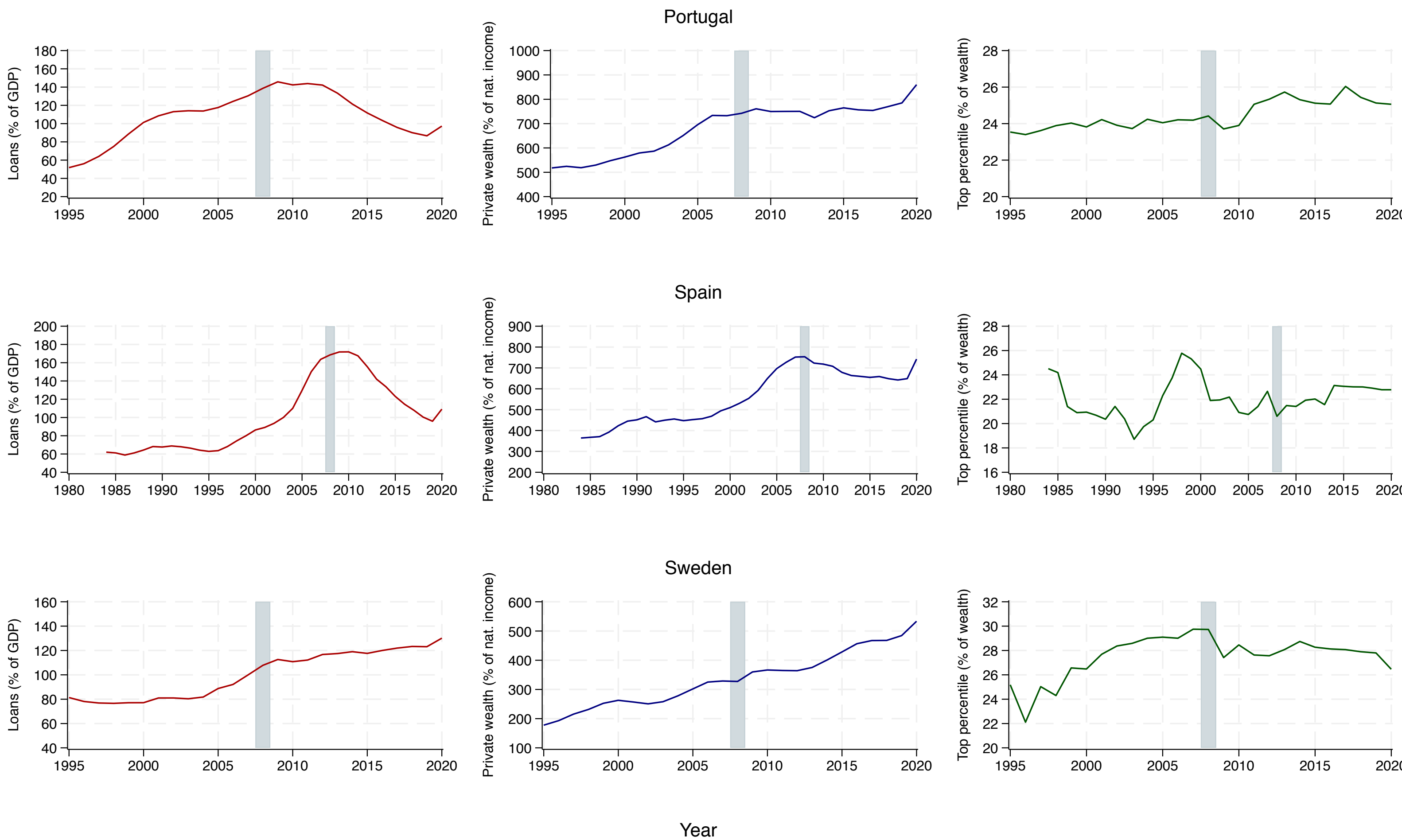
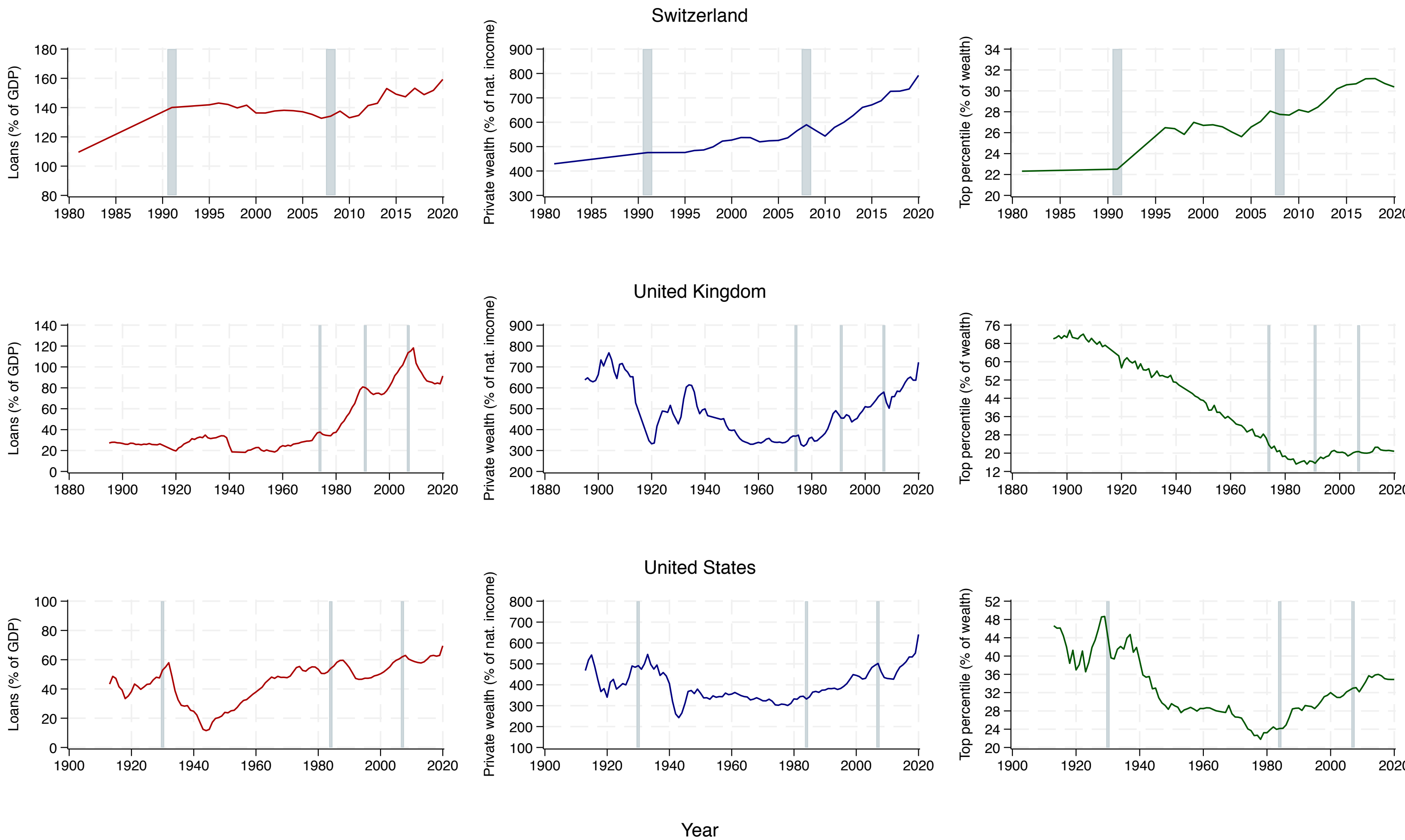


Figure 1: Credit, wealth concentration and financial crises (continued)

(a) Loans/GDP ((b)) Wealth/Income ((c)) Top 1%



Notes: This figure illustrates the trends in the share of total loans to the non-financial private sector relative to GDP, the share of private wealth in national income, and the share of wealth held by the top 1% across the 18 countries in our sample. The time periods vary by country based on the availability of data for all three variables. The shaded areas represent the first year of a financial crisis event, as documented in the Jordà-Schularick-Taylor financial crisis chronology from the Macrohistory Database. *Source*: Own estimations using data from the Macrohistory Database and WID.

3.2 Additional controls

In addition to credit growth, we control for other factors recognized in the literature as significant predictors of financial crises. For example, along with credit expansion, asset price growth is another key factor in crisis prediction (Sufi and Taylor, 2022).[7] Accordingly, we deflate nominal house and equity prices using the CPI and include the growth in real house and equity prices as additional control variables.

Schularick and Taylor (2012) find that, following World War II, while credit grew more rapidly than broad money, the latter still serves as a useful proxy for the former. According to economic theory, changes in interest play a crucial role in influencing money supply. Some studies have identified rising interest rates, allegedly implemented to defend a currency peg, as significant predictors of financial crises (Caprio and Klingebiel, 1996; Demirgüç-Kunt and Detragiache, 1998; Hardy and Pazarbaşioğlu, 1999; Gourinchas et al., 2001; Eichengreen and Arteta, 2002). In contrast, using data from 14 developed countries over a 140-year period, Jordà et al. (2011) highlight that low short-term interest rates relative to growth rates are a characteristic feature of periods preceding global financial crises. Although they confirm that credit expansion is the most important predictor, they also find that accounting for external imbalances, as captured by the current account, enhances long-term crisis predictability. Furthermore, Gourinchas et al. (2001) discuss the boom-bust cycle of the current account and Kiley (2021) emphasizes current account deficits as conditions conducive to financial crises. Therefore, we control for the growth in real broad money, real short-term interest rates, and the current account-to-GDP ratio.

Several early studies in this strand of literature find that the worsening of the real sector, marked by a decline in real GDP, could also trigger a crisis (see Demirgüç-Kunt and Detragiache, 1998; Hutchison and McDill, 1999; Hardy and Pazarbaşioğlu, 1999; Glick and Hutchison, 2001; Eichengreen and Arteta, 2002). Others refer to insufficient, volatile or

[7] See also Hutchison and McDill (1999), Kaminsky and Reinhart (1999), Jordà et al. (2015a), Greenwood et al. (2022), and Richter et al. (2021).

unproductive investments as another important factor (Gourinchas et al., 2001; Schularick and Taylor, 2012; Richter et al., 2021). We therefore include the growth in real GDP per capita and investment-to-GDP ratio to control for these competing narratives.

Other studies emphasize the importance of analyzing various components of bank balance sheets. Caprio and Klingebiel (1996) highlight low bank capitalization levels as a condition that contributes to insolvency. Although Jordà et al. (2021) do not find a direct association between higher capital ratios and a lower risk of banking crises, Richter et al. (2021) find that a higher capital ratio increases the likelihood of credit booms, which they refer to as "bad booms," that trigger crises. Additionally, they show that a rising loan-to-deposit ratio, coupled with credit and house price booms, increases the likelihood of systemic bank runs. Therefore, we control for the growth in the capital ratio of banks, defined as capital over total assets, and the loan-to-deposit ratio.

3.3 Empirical estimation of asset price bubbles

Given that asset price growth is a key driver of wealth accumulation (Piketty and Zucman, 2014) and, alongside credit expansion, a major trigger of crises (Sufi and Taylor, 2022), we explore whether it could act as a transmission channel. Specifically, we examine whether changes in private wealth accumulation and wealth inequality signal shifts in the probability of asset price bubbles. Since these bubbles often burst, they can ultimately lead to financial crises.

We adopt the term "bubble" to describe a scenario "when asset prices deviate from their fundamental value in an asymmetric and explosive manner, often followed by a subsequent crash" (Jordà et al., 2015b, p. 6). Consistent with this definition, the empirical literature commonly estimates asset bubbles by identifying significant price deviations from specific thresholds (e.g., Borio and Lowe, 2002; Detken and Smets, 2004; Goodhart and Hofmann, 2008; Jordà et al., 2015b). In line with this approach, our main definition of the signal for an asset price bubble is when, in any given country, the log of the real asset price rises by more than one standard deviation from its trend. We obtain the trend by removing the cyclical component using the Hodrick–Prescott filter.[8] Given the availability of data on house and equity prices, we differentiate between house and equity price bubbles.

Although this definition is commonly used in the literature, there is no consensus on a single method to empirically identify asset price bubbles. Jordà et al. (2015b) propose an alternative approach, in which, alongside the "price elevation" characterized by a more than one standard deviation price increase, a bubble is also defined by a subsequent "price correction" or "bubble burst." Specifically, this occurs when prices drop by at least 15% within a 3-year window following the initial price surge. We adopt this alternative definition of asset price bubbles to further test the robustness of our results. Table 1 presents the descriptive statistics for all variables used in our main analysis of financial crises, as well as those employed to examine whether asset price bubbles serve as a transmission channel.

Figure 2 shows the trends of house and equity prices in each country, the estimated bubble signals using our main approach, and the episodes of financial crises depicted by the shaded areas. Again, trends are shown only for periods in which data on all variables—asset prices, the private wealth-income ratio, and the share of wealth held by the top 1%—are available. Although we identify signals that do not culminate in financial crises, our main approach demonstrates that no financial crisis in our sample occurs without prior detection of asset price bubbles. For example, we are able to detect house price bubble signals several years before the beginning of the GFC. Focusing on key actors involved, we observe early indications starting in 2003 in the UK, 2005 in the US and Ireland, and 2006 in Spain. Additionally, we identify equity price bubble signals before other financial crises, such as those in 1917 leading up to the 1921 crisis in the Netherlands and those emerging in 1927 and 1928 in the US and France, respectively, preceding the financial crisis triggered by the Great Crash.

[8] Since our data is annual, we apply a smoothing parameter λ of 100.

Table 1: Descriptive statistics

	Mean	SD	Min	Max	N
Δ log Top 1%	-0.002	0.043	-0.210	0.171	799
Δ log W/Y	0.006	0.065	-0.958	0.764	1,401
Δ log real Loans	0.044	0.109	-1.675	1.321	2,439
Δ log Loans/GDP	0.015	0.093	-0.864	1.392	2,415
Δ log real House prices	0.013	0.119	-2.096	0.756	2,026
Δ log real Equity prices	0.006	0.216	-2.508	0.866	2,229
Δ log real Broad money	0.035	0.162	-6.903	0.706	2,493
Δ log real GDP per capita	0.018	0.050	-0.711	0.506	2,648
Δ log Investment/GDP	0.006	0.129	-1.455	1.076	2,391
Δ log Capital ratio (banks)	-0.009	0.094	-0.612	1.035	2,331
Δ log Loans/Deposits (banks)	-0.001	0.080	-0.566	0.564	2,277
Δ Short-term interest rate	-0.043	1.323	-10.781	7.688	2,477
Δ Current account/GDP	0.000	0.025	-0.266	0.187	2,451
Financial crisis (JST)	0.033	0.179	0	1	2,668
Financial crisis (RR)	0.039	0.194	0	1	2,538
Financial crisis (BVX)	0.044	0.206	0	1	2,646
Financial crisis (BVXN)	0.045	0.207	0	1	2,646
House price bubble (main)	0.122	0.327	0	1	2,050
House price bubble (alternative)	0.067	0.250	0	1	2,050
Equity price bubble (main)	0.140	0.347	0	1	2,250
Equity price bubble (alternative)	0.117	0.322	0	1	2,250

Notes: Top 1% denotes the share of wealth held by the top percentile of the wealth distribution. W/Y represents the ratio of private wealth to national income. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). The main definition of house and equity price bubbles identifies years in which the log of their respective prices rises by more than one standard deviation from their Hodrick-Prescott filtered trend. Following Jordà et al. (2015b), the alternative definition also requires a price drop of at least 15% within a 3-year window following the initial surge. See Section 3 for detailed definitions of all variables. *Source*: Own estimations using data from the Macrohistory Database and WID.

Figure 2: Asset prices and estimated bubbles

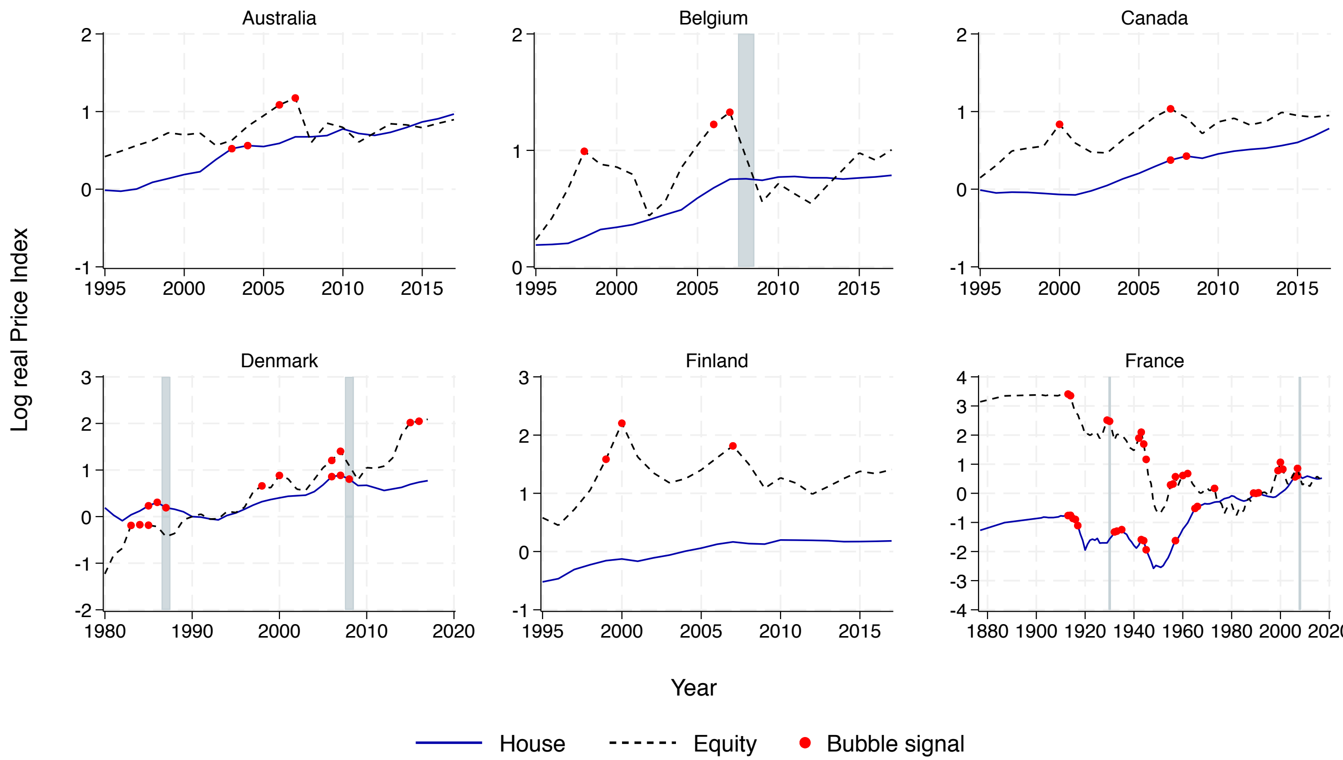


Figure 2: Asset prices and estimated bubbles (continued)

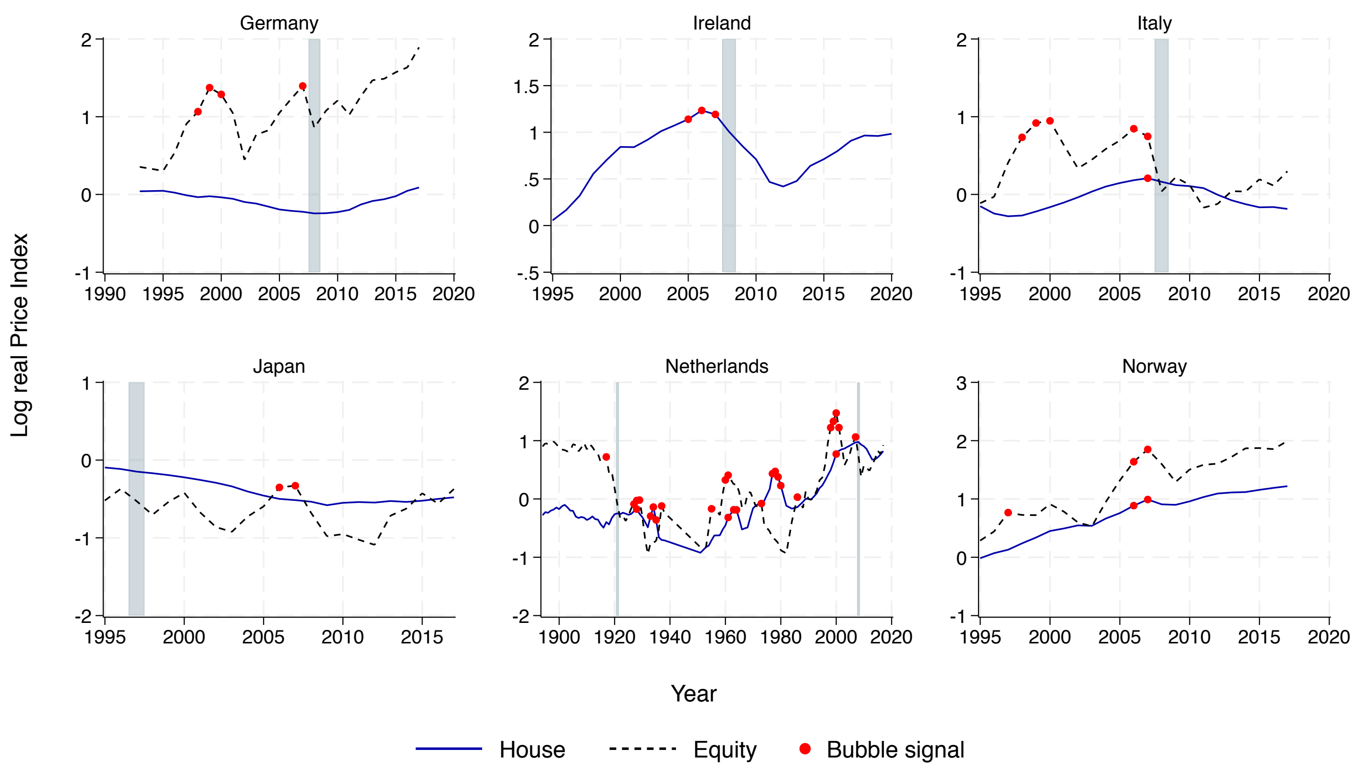
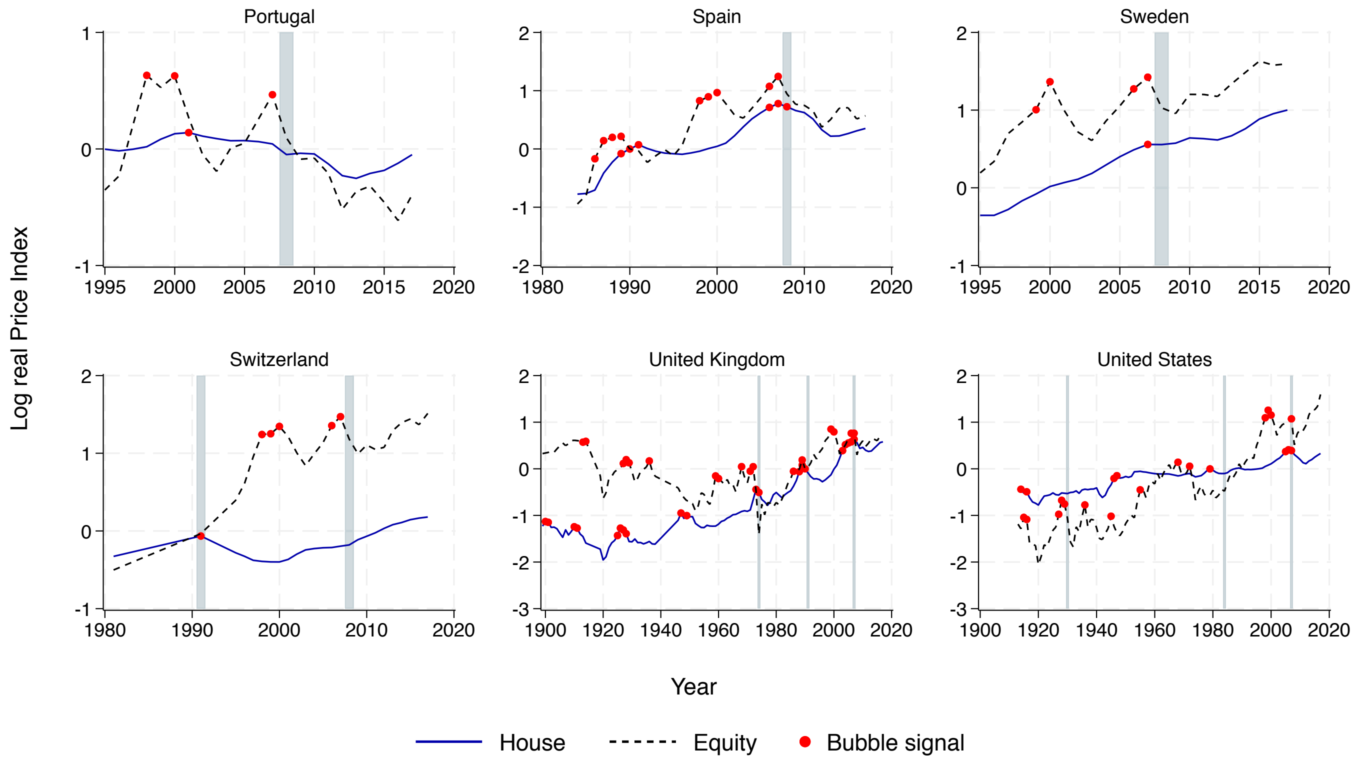


Figure 2: Asset prices and estimated bubbles (continued)



Notes: This figure illustrates the trends in real house and equity prices, calculated by deflating the logarithmic form of their indices using the CPI. Red dots mark bubble signals, defined as years when the log of real house or equity prices increases by more than one standard deviation from their Hodrick-Prescott filtered trend. The shaded areas represent the first year of a financial crisis event, as identified in the Jordà-Schularick-Taylor financial crisis chronology. Note that equity price data for Ireland are unavailable. *Source*: Own estimations using data from the Macrohistory Database and WID.

4 Empirical strategy

4.1 Main approach

Our aim is to test the relationship between wealth inequality and financial crises. Following standard practices in the literature on the determinants of financial crises, we employ a logit model similar to the preferred specification of Schularick and Taylor (2012). Using our long-run annual dataset covering 18 countries, we specify a probabilistic model in terms of the log-odds ratio of a financial crisis occurring in country i during year t as

$$\text{logit}(p_{it}) = \beta_1 \Delta Credit_{it-k} + \beta_2 \Delta(\frac{W}{Y})_{it-k} + \beta_3 \Delta Top1\%_{it-k} + \gamma \Delta \boldsymbol{X}_{it-1} + \mu_i + \epsilon_{it} \qquad (1)$$

where Δ represents the annual change calculated as the first difference of the variable,[9] $Credit$ is the total loans to non-financial private sector deflated by the CPI, $\frac{W}{Y}$ is the ratio of private wealth to national income, $Top1\%$ is the share of wealth held by the top 1%. Controls are denoted by the vector $\boldsymbol{X}$ and include real GDP per capita, investment-to-GDP ratio, current account-to-GDP ratio, real broad money, real short-term interest rates, banks' capital ratio, banks' loans-to-deposits ratios, real house prices, and real equity prices. All independent variables, except the current account-to-GDP ratio and short-term interest rates, which contain negative values too, are log-transformed. We assume that the error term ϵ_{it} satisfies the standard assumptions.

Following Schularick and Taylor (2012), we use five lags of the three main variables, indicated by $t-k$ where, $k = 1, ..., 5$.[10] We follow this approach because, first, as noted by Schularick and Taylor (2012), "credit booms are typically considered phenomena that last for many years" (p. 1044). Second, compared to the dynamics of income inequality, changes in wealth inequality take longer. For example, accumulating savings, realizing capital gains, or inheriting wealth are processes that generally require longer time horizons.

[9] This is done to exclude stochastic or non-stationary trends.

[10] When we analyze the relationship between wealth accumulation, wealth inequality and asset price bubbles, we use only one lag to adhere to a simple lag structure for testing the transmission channel.

Because we also include country fixed effects, denoted by μ_i, we note that this raises the incidental parameters problem originally introduced by Neyman and Scott (1948). Unlike in linear specifications, when employing a nonlinear model such as logit—our chosen approach—estimating both the fixed effects and the parameters β at the same time does not lead to a consistent estimator of β when T is fixed and $N \to \infty$ (Wooldridge, 2010, p. 484). However, as in Schularick and Taylor (2012), our dataset contains a small number of countries over a long period of time, which is the case where $T > N$, and as $T \to \infty$, the bias attenuates.[11] Although the literature lacks consensus on the threshold for a sufficiently large T, in the final model, the shortest period covered in a country is 18 years and the longest is 100 years, with an average $T > 40$. Thus, we include country fixed effects to control for time-invariant heterogeneity and account for within-country variation.

Although we work with a long panel, we do not include time fixed effects to avoid losing many observations, as several years in our sample have no financial crisis episodes. For the same reason, similar studies such as Schularick and Taylor (2012) and Kirschenmann et al. (2016) choose not to include year fixed effects in their nonlinear specifications, and Hauner (2020) employs a linear probability model as the main empirical approach. Nevertheless, we add year fixed effects in the robustness check section, where we apply an alternative empirical strategy.

4.2 Alternative method

Among the different robustness checks that we perform, we estimate impulse response functions through local projections (LP) as suggested in Jordà (2005). The basic idea is to assess how a shock in wealth inequality in the present influences the probability of a financial crisis in the future, relative to a baseline where inequality remains constant. As in our main specification, we first estimate LP using a logit model with country fixed effects. To further test the robustness of our results, we employ a two-way fixed effects linear probability model,

[11] Using Monte Carlo methods, Greene (2004) shows that the small sample bias in probit and logit models "drops off rapidly as T increases to three or more" (p. 115).

incorporating year fixed effects as well.

We define a shock in W as a 1% increase in either the growth of (i) the private wealth-income ratio or (ii) the share of wealth held by the top 1%, both of which are log-transformed. The linear probability model (LPM) with the financial crisis FC as a binary outcome is then specified as a LP given by

$$FC_{i,t+h} = \sum_{k=1}^{5} \beta^h \Delta W_{i,t-k} + \gamma^h \Delta \boldsymbol{X}_{i,t-1} + \mu_i^h + \delta_t^h + \epsilon_{i,t+h}, \quad h = 0, 1, ..., H, \tag{2}$$

where $\boldsymbol{X}$ denotes the same controls as in the main analysis, including the share of wealth held by the top 1% when the shock is in (i) and the private-wealth income ratio when the shock is in (ii). Country and year fixed effects at horizon h are denoted by μ_i^h and δ_t^h, respectively. We include five lags of our main variable of interest and project over a horizon of five years.

5 Results

5.1 Wealth concentration and financial crises

The main results of estimating the probability of a financial crisis based on a rise in wealth inequality are shown first. Table 2 presents the results of logit regressions. In columns (1) and (2), we replicate the results of Schularick and Taylor (2012) by estimating the probability of a financial crisis based only on credit growth. Column (1) presents results where we include real loans as the single independent variable, while in column (2) we add country fixed effects, thus replicating the baseline model in Schularick and Taylor (2012).

We follow the same logic in columns (3) and (4), but instead of real loans, we focus solely on the private wealth-income ratio. Column (5) presents the results using only the share of wealth held by the top 1%. Column (6) incorporates country fixed effects. Column (7) displays the results with all three variables—private wealth-income ratio, share of wealth held by the top 1%, and real loans—without country fixed effects, which are added in column (8). The final model in column (9) includes both country fixed effects and several additional factors commonly found in the literature as potential determinants of financial crises. They include the growth in real GDP per capita, investment-to-GDP ratio, current account-to-GDP ratio, real broad money, real short-term interest rates, banks' capital ratios, banks' loans-to-deposits ratios, real house prices, and real equity prices.

First, we replicate the results of Schularick and Taylor (2012) to reaffirm the role of credit growth as a key trigger of financial crises. Our results in column (2) are very similar to what Schularick and Taylor (2012) consider their preferred baseline specification. We also find that the first lag of credit growth is small, negative, and statistically insignificant, while the second lag is large, positive, and highly significant, "confirming that when the second derivative of credit changes sign we can see that trouble is likely to follow (Biggs et al., 2009)" (as cited in Schularick and Taylor, 2012, p. 1046). In our case, the magnitude of the sum of lags is slightly lower 0.23 compared to 0.301 found in Schularick and Taylor (2012), mainly because we have more countries (18 versus 14) and observations (2,318 versus 1,272).

Another important finding arises from comparing these replicated results with the results for our wealth variables. In the single variable regressions with country fixed effects, as shown in columns (4) and (6), both the growth of the W/Y and the top 1% wealth share have positive and statistically significant coefficients of certain lags. In the case of growth in W/Y, the second, third, and fourth lags are significant. The magnitude of the second lag is comparable to that of the credit growth; however, one should note that we lose two countries and the number of observations is much lower because of missing data for certain years.

Similar results are found in the case of the rise in wealth inequality, measured by the growth in the share of wealth held by the top 1%. As shown in column (6), the second lag is positive and significant at the 10% level. Again, the number of countries and observations is further reduced because the data on the top 1% wealth share are even scarcer. Bearing in mind these sample restrictions, these results present early indications that an increase in wealth inequality is indeed associated with an increase in the probability of financial crises.

Because we do not claim that an increase in wealth inequality is the sole or the main factor in increasing the likelihood of a financial crisis, we take into account other factors that the literature on the determinants of financial crises recognizes as important predictors. So, in column (7), we include the credit growth and the growth in the private wealth-income ratio, and in column (8) we add country fixed effects. In the final specification, in column (9) we add all the aforementioned controls which represent relevant predictors of financial crises.

Our main finding here is that even after controlling for the most important predictors of financial crises and country fixed effects, an increase in wealth inequality is associated with an increase in the likelihood of financial crises. Two important changes in our final model compared to the single variable regressions are (i) increases in the magnitude of most of coefficients and (ii) changes in the significance levels of certain lags. In this model, the first lag of credit growth now becomes significant and it almost quadruples compared to the second lag in the baseline model in column (2). The first lag in W/Y growth now becomes statistically significant and negative, but is smaller in magnitude than that of credit growth. The third and fourth lags remain positive and significant and show higher magnitudes. The second lag in wealth inequality growth remains positive and its magnitude and significance level increase.

These results suggest that there are different temporal relationships between each of these factors and the likelihood of a financial crisis. For example, a credit boom can jeopardize the financial system as early as the following year. In contrast, it takes three or four years for an increase in wealth accumulation to significantly raise the probability of a systemic bank run. Similarly, it takes a couple of years for a growing wealth concentration at the top of distribution to trouble the financial stability of a country.

Table 2: Wealth concentration and financial crises

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ log real Loans$_{t-1}$	0.481	0.412					8.414*	12.617**	32.242***
	(1.173)	(1.230)					(4.299)	(4.911)	(11.421)
Δ log real Loans$_{t-2}$	6.583***	6.806***					6.365	7.402	-0.760
	(1.417)	(1.643)					(6.378)	(6.585)	(7.313)
Δ log real Loans$_{t-3}$	-0.448	-0.500					-0.518	-0.381	12.563
	(0.750)	(0.759)					(5.121)	(6.593)	(7.937)
Δ log real Loans$_{t-4}$	-0.113	0.026					3.725	4.460	-12.109
	(0.908)	(1.095)					(6.943)	(8.969)	(13.468)
Δ log real Loans$_{t-5}$	1.121	1.137					-1.802	0.287	0.396
	(0.689)	(0.786)					(6.505)	(6.676)	(6.528)
Δ log (W/Y)$_{t-1}$			1.471	1.473			-8.737**	-10.921**	-19.797***
			(3.553)	(3.553)			(3.819)	(5.288)	(6.774)
Δ log (W/Y)$_{t-2}$			5.876**	5.632**			9.288	11.892	19.889
			(2.756)	(2.775)			(10.076)	(11.438)	(13.878)
Δ log (W/Y)$_{t-3}$			4.841**	4.771**			9.135***	11.758**	23.408***
			(2.051)	(2.016)			(3.319)	(4.948)	(7.668)
Δ log (W/Y)$_{t-4}$			3.233*	3.251*			10.017***	12.054**	39.282***
			(1.850)	(1.878)			(3.312)	(5.250)	(10.273)
Δ log (W/Y)$_{t-5}$			0.250	0.047			-4.312	-4.119	-12.951
			(1.222)	(1.177)			(3.826)	(5.063)	(10.282)
Δ log Top 1%$_{t-1}$					1.489	1.952	4.661*	7.390***	4.603
					(2.745)	(2.987)	(2.568)	(2.855)	(5.142)
Δ log Top 1%$_{t-2}$					14.093**	14.493*	19.104**	24.293***	42.433***
					(6.463)	(7.857)	(7.505)	(8.424)	(14.211)
Δ log Top 1%$_{t-3}$					-5.014	-4.915	-0.712	0.970	-1.385
					(3.661)	(3.783)	(4.814)	(5.318)	(6.324)
Δ log Top 1%$_{t-4}$					5.365	5.102	3.633	6.381	-1.003
					(6.143)	(6.529)	(5.903)	(8.009)	(12.517)
Δ log Top 1%$_{t-5}$					-1.218	-0.980	-0.289	-0.302	-1.168
					(3.768)	(4.197)	(3.716)	(4.908)	(9.380)
Joint sign. of lags, χ^2:									
Δ log real Loans	82.952	51.413					7.902	16.004	9.189
p-value	0.000	0.000					0.095	0.003	0.057
Δ log (W/Y)			9.095	9.605			66.709	48.052	25.154
p-value			0.105	0.087			0.000	0.000	0.000
Δ log Top 1%					20.338	11.581	84.954	30.054	67.510
p-value					0.001	0.041	0.000	0.000	0.000
N	2,318	2,318	1,303	1,239	667	567	648	550	481
Countries	18	18	18	16	18	13	18	13	12
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Controls	No	No	No	No	No	No	No	No	Yes
Pseudo R^2	0.056	0.078	0.031	0.040	0.054	0.071	0.243	0.294	0.517
Pseudolikelihood	-306.020	-298.905	-163.070	-159.641	-81.675	-77.303	-64.924	-58.295	-35.491
AUC	0.697	0.710	0.643	0.653	0.725	0.733	0.869	0.901	0.961
Standard error	0.030	0.030	0.051	0.052	0.045	0.052	0.042	0.026	0.015

Notes: This table presents the results from logit models for systemic banking crises, emphasizing wealth inequality as the main variable of interest, along with other key factors. The dependent variable is set to 1 in the first year of a financial crisis event and 0 otherwise. Δ represents the annual change, calculated as the first difference of the variable. W/Y denotes the private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. Controls include the change in (i) real GDP per capita, (ii) investment-to-GDP ratio, (iii) current account-to-GDP ratio, (iv) real broad money, (v) real short-term interest rates, (vi) banks' capital ratios, (vii) banks' loans-to-deposits ratios, (viii) real house prices, and (ix) real equity prices. Except for the current account-to-GDP ratio and short-term interest rates, which may contain negative values, all variables are log-transformed. Each control variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, and the test statistics for the joint significance of the lags of the three variables shown in the table, are displayed at the bottom. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Interestingly, the negative value of the first lag of the growth of W/Y indicates a decrease in the likelihood of a crisis, potentially due to increased savings which enhance the liquidity of banks. In the short term, controlling for credit expansion and other relevant factors to the financial stability, this heightened liquidity could reduce the risk of a bank run. In summary, while higher wealth accumulation and greater wealth concentration do not pose an immediate threat to financial stability, they appear to introduce a lagged risk that may take a few years to manifest.

From an economic perspective, we are interested in quantifying these effects in the probability of financial crises. In Table 3, we present the average marginal effects of each coefficient for the lags shown in column (9) of Table 2. To provide a more intuitive depiction, we rearrange the sets of lags into separate columns: the five lags of credit growth are presented in column (1), the lags of growth in W/Y are displayed in column (2), and the lags of growth in the top 1% wealth share are presented in column (3).

Table 3: Average marginal effects for the final model in Table 2

	Δ log real Loans	Δ log (W/Y)	Δ log Top 1%
	(1)	(2)	(3)
$t-1$	0.694***	-0.426***	0.099
	(0.195)	(0.122)	(0.109)
$t-2$	-0.016	0.428	0.913***
	(0.157)	(0.293)	(0.263)
$t-3$	0.270*	0.504***	-0.030
	(0.151)	(0.135)	(0.134)
$t-4$	-0.261	0.845***	-0.022
	(0.288)	(0.180)	(0.269)
$t-5$	0.009	-0.279	-0.025
	(0.141)	(0.211)	(0.201)
N	481	481	481
Countries	12	12	12
Sum of lags	0.696	1.072	0.936
Standard error	0.271	0.526	0.244
p-value	0.010	0.041	0.000

Notes: This table presents the average marginal effects (AME) from estimates in Column (9) of Table 2, with five lags of each variable shown in separate columns. Column (1) reports the AME for the change in log real loans, column (2) for the change in log private wealth-income ratio, and column (3) for the change in the wealth share of the top 1%. The sum of the lags, along with its standard error and p-value, is also reported. Country-clustered robust standard errors are shown in parentheses. *p <0.10, **p <0.05, ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

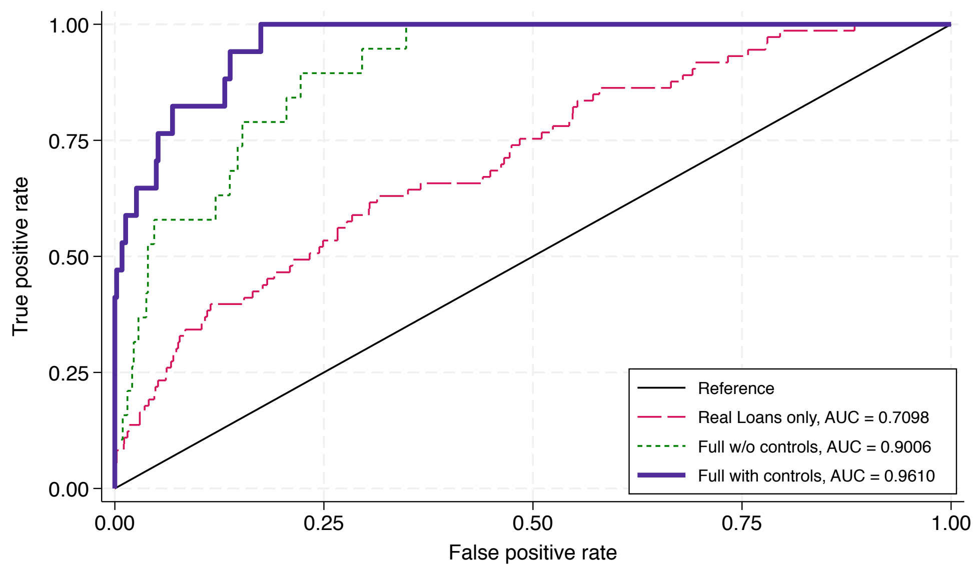
Given that all of our independent variables are continuous, we standardize their coefficients in order to provide a more meaningful interpretation. In our sample in the final model, the average real loan growth over five years has a standard deviation of about 0.06. All else equal, a one standard deviation increase in real loan growth is associated with a 4.2 pp rise in the probability of a financial crisis, which is statistically significant at the 5% level. We note that this is a considerable increase compared to the baseline used by Schularick and Taylor (2012), which is about 2.3 pp. In that model, though, there are no other controls except for country fixed effects. In other words, accounting for other important macroeconomic and financial factors, credit expansion is associated with an even higher probability of systemic bank runs.

We find that private wealth accumulation and wealth inequality also play a considerable role. In the sample of our final model, the average growth of W/Y over five years has a standard deviation of about 0.048. Controlling for other factors, a one standard deviation rise in the growth of W/Y is associated with a 5.2 pp increase in the probability of a crisis, which is significant at the 5% level. Finally, in the same sample, the average five-year growth in the top 1% wealth share has a standard deviation of approximately 0.048. All else equal, a one standard deviation rise in the growth the top 1% wealth share is associated with a 4.5 pp increase in the probability of a financial crisis, which is significant at the 1% level.

How good is our model for predicting financial crises? As shown in Table 2, to assess the goodness of fit for each model, we estimate the AUC, which is the area under the receiver operating characteristic curve (ROC). This statistic measures the ability of our model to correctly classify the occurrence of financial crises based on combinations of true positive and false positive rates as shown in Figure 3. The reference line of AUC is 0.5, which would mean that the predictive power of the model for detecting an episode of financial crisis is no better than a coin toss. In contrast, a value of 1 would mean that the model is able to perfectly predict financial crisis episodes.

As shown in Figure 3, when we include the growth in W/Y and the share of wealth held by the top 1% in addition to credit growth, the AUC rises considerably, indicating a model with much better predictive power. The AUC of the replicated baseline model from Schularick and Taylor (2012) is around 0.71, which we can use as a baseline to evaluate the rest of the models.[12] Once we include the two variables related to wealth, without additional controls, the AUC jumps to about 0.91. The additional controls further improve the predictive power, though by a smaller margin.

Figure 3: Classification of financial crises from Table 2



Notes: This figure shows the area under the receiver operating characteristic curve (AUC) for the models presented in Table 2. AUC values are reported for three models: column (2), which includes growth in real loans and country fixed effects; column (8), which adds the growth in the private wealth-income ratio and top 1% wealth share; and column (9), which includes additional controls. *Source*: Own estimations using data from the Macrohistory Database and WID.

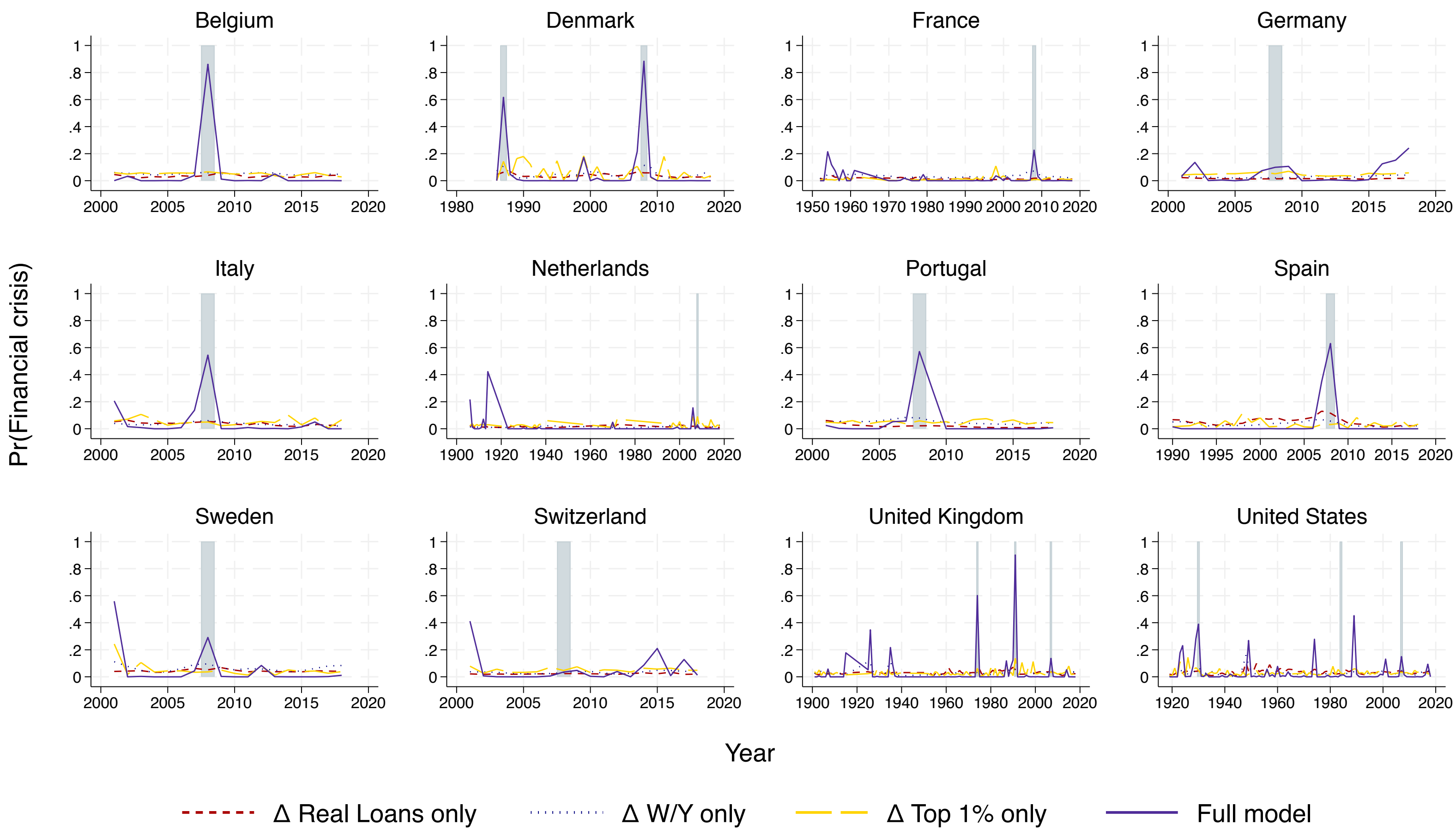
Lastly, we compare how well different models predict financial crisis episodes individually in each country. We compare single-variable models with country fixed effects (i.e. baseline models), where only growth in real loans, the W/Y or the top 1% wealth share is included, and the final model. Figure 4 shows the predicted probabilities for each financial crisis in

[12] As shown in column (4) of Table 2, when we use the W/Y with country fixed effects, we obtain an AUC of 0.653, which indicates that, compared to credit growth, the growth in W/Y has less predictive power. However, when we use the growth in the share of wealth held by the top 1%, as shown in column (6), the AUC increases to around 0.733. A caveat here is that, the time span for most countries is shorter than in the baseline model.

each country included in our final sample.

In total, we cover 17 episodes of financial crises, 12 of which represent the GFC in Belgium, Denmark, France, Germany, Italy, the Netherlands, Portugal, Spain, Sweden, Switzerland, the UK and the US. Other notable episodes include the systemic financial crisis in the US in 1930, which was a consequence of the stock market crash in 1929 and marked the onset of the Great Depression, and the crisis of 1984. Additionally, we cover the Secondary Banking Crisis of 1974 and the crisis of 1991 in the UK as well as the 1987 crisis in Denmark. In all cases, our final model predicts a higher probability of a financial crisis compared to the baseline model of Schularick and Taylor (2012) or the baseline models that include either the growth in W/Y or the top 1% wealth share, without additional controls except for country fixed effects.

Figure 4: Prediction of financial crises



Notes: This figure shows the probabilities of financial crises for each country in our final sample, as predicted by different models from Table 2. It compares the in-sample predictions from the model in column (2), which includes growth in real loans and country fixed effects; column (4), which adds growth in the private wealth-income ratio and country fixed effects; column (6), which includes the growth in the share of wealth held by the top 1% along with country fixed effects; and the final model in column (9), which combines all three variables with additional controls and country fixed effects. The shaded areas represent the first year of a financial crisis event, as identified in the Jordà-Schularick-Taylor financial crisis chronology. *Source*: Own estimations using data from the Macrohistory Database and WID.

5.2 Robustness checks for main results

We perform a number of robustness checks for our main results by (i) defining credit growth differently, (ii) using alternative definitions of financial crisis, (iii) restricting the sample to different time periods and (iv) employing an alternative empirical strategy.

Alternative definition of credit growth. First, instead of defining credit using real loans, we use the loans-to-GDP ratio, which is another standard measure of credit in the literature (Sufi and Taylor, 2022). Table 4 shows these results. Except for small differences in effect sizes, we obtain similar results.

In Table 5, we present the average marginal effects based on the results from the final model in Table 4. The findings indicate that, controlling for all other variables, a one standard deviation increase in the growth of the loans-to-GDP ratio is associated with a 3.8 pp increase in the probability of a financial crisis. This result is statistically significant at the 1% level. The corresponding estimates for the growth in W/Y and the top 1% wealth share are 4.5 pp (at the 10% significance level) and 3.8 pp (at the 1% significance level), respectively.

To assess the predictive power of different models, Figure 6 compares the AUC statistics of three models presented in Table 4, following the approach in Figure 3. The change in the definition of credit growth leads to a slight increase in the AUC, from approximately 0.71 to 0.72. Including the growth in W/Y and the top 1% wealth share further raises the AUC to around 0.90. Adding additional controls increases the AUC to 0.96, indicating a further improvement in predictive power. These results suggest that the incorporation of indicators of private wealth accumulation and wealth inequality considerably enhances the predictive accuracy of the model, even when using the more widely accepted definition of credit growth in the literature, as opposed to the measure preferred by Schularick and Taylor (2012).

Table 4: Wealth concentration, loans-to-GDP ratio, and financial crises

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ log (Loans/GDP)$_{t-1}$	2.660	2.537					9.747**	13.632***	27.665**
	(2.143)	(2.330)					(3.986)	(4.640)	(13.061)
Δ log (Loans/GDP)$_{t-2}$	5.798***	5.855***					1.366	1.427	-2.077
	(1.546)	(1.600)					(4.335)	(5.144)	(8.792)
Δ log (Loans/GDP)$_{t-3}$	2.001	1.992					5.033	5.911	11.251
	(1.786)	(1.852)					(3.164)	(4.046)	(9.138)
Δ log (Loans/GDP)$_{t-4}$	-1.143	-1.185					-1.956	-0.855	-14.395*
	(1.435)	(1.492)					(4.232)	(5.203)	(7.420)
Δ log (Loans/GDP)$_{t-5}$	0.340	0.374					5.340	6.689	7.517*
	(0.718)	(0.728)					(3.858)	(4.068)	(4.464)
Δ log (W/Y)$_{t-1}$			1.471	1.473			-10.104***	-14.079**	-19.885**
			(3.553)	(3.553)			(3.893)	(5.821)	(10.044)
Δ log (W/Y)$_{t-2}$			5.876**	5.632**			17.671**	22.088***	22.057*
			(2.756)	(2.775)			(6.934)	(8.095)	(13.298)
Δ log (W/Y)$_{t-3}$			4.841**	4.771**			10.574***	12.907**	22.252**
			(2.051)	(2.016)			(3.877)	(5.525)	(9.914)
Δ log (W/Y)$_{t-4}$			3.233*	3.251*			9.512***	10.898**	35.109***
			(1.850)	(1.878)			(3.663)	(4.941)	(8.710)
Δ log (W/Y)$_{t-5}$			0.250	0.047			-4.150	-5.090	-16.671
			(1.222)	(1.177)			(3.600)	(5.171)	(11.242)
Δ log Top 1%$_{t-1}$					1.489	1.952	4.946*	7.639**	3.930
					(2.745)	(2.987)	(2.983)	(3.630)	(6.479)
Δ log Top 1%$_{t-2}$					14.093**	14.493*	20.317***	26.657***	40.711***
					(6.463)	(7.857)	(7.458)	(8.299)	(11.017)
Δ log Top 1%$_{t-3}$					-5.014	-4.915	1.156	2.152	-2.991
					(3.661)	(3.783)	(3.248)	(3.887)	(6.468)
Δ log Top 1%$_{t-4}$					5.365	5.102	2.892	4.481	-0.854
					(6.143)	(6.529)	(4.931)	(7.242)	(13.231)
Δ log Top 1%$_{t-5}$					-1.218	-0.980	-1.259	-2.751	-4.380
					(3.768)	(4.197)	(4.223)	(5.862)	(9.163)
Joint sign. of lags, χ^2:									
Δ log (Loans/GDP)	56.173	48.085					13.760	18.076	24.977
p-value	0.000	0.000					0.008	0.001	0.000
Δ log (W/Y)			9.095	9.605			37.913	23.542	24.471
p-value			0.105	0.087			0.000	0.000	0.000
Δ log Top 1%					20.338	11.581	55.061	26.728	34.253
p-value					0.001	0.041	0.000	0.000	0.000
N	2,278	2,278	1,303	1,239	667	567	636	538	477
Countries	18	18	18	16	18	13	18	13	12
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Controls	No	No	No	No	No	No	No	No	Yes
Pseudo R^2	0.053	0.075	0.031	0.040	0.054	0.071	0.258	0.302	0.511
Pseudolikelihood	-302.688	-295.445	-163.070	-159.641	-81.675	-77.303	-60.805	-55.000	-35.907
AUC	0.698	0.716	0.643	0.653	0.725	0.733	0.860	0.896	0.961
Standard error	0.034	0.032	0.051	0.052	0.045	0.052	0.049	0.031	0.017

Notes: This table presents the results from logit models for systemic banking crises, emphasizing wealth inequality as the main variable of interest, along with other key factors. The dependent variable is set to 1 in the first year of a financial crisis event and 0 otherwise. Δ represents the annual change, calculated as the first difference of the variable. W/Y denotes the private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 2 are included. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, and the test statistics for the joint significance of the lags of the three variables shown in the table, are displayed at the bottom. Country-clustered robust standard errors are reported in parentheses. $^*p<0.10$, $^{**}p<0.05$, and $^{***}p<0.01$. *Source*: Own estimations using data from the Macrohistory Database and WID.

Table 5: Average marginal effects for the final model in Table 4

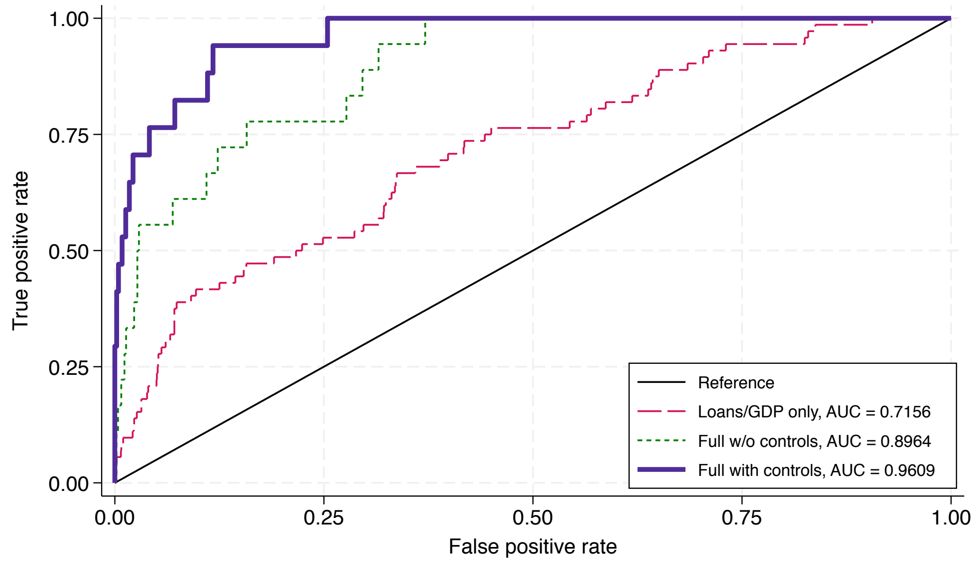
	Δ log (Loans/GDP)	Δ log (W/Y)	Δ log Top 1%
	(1)	(2)	(3)
$t-1$	0.605**	-0.435**	0.086
	(0.250)	(0.196)	(0.137)
$t-2$	-0.045	0.482*	0.890***
	(0.190)	(0.279)	(0.223)
$t-3$	0.246	0.486**	-0.065
	(0.182)	(0.192)	(0.139)
$t-4$	-0.315**	0.768***	-0.019
	(0.156)	(0.175)	(0.289)
$t-5$	0.164	-0.364	-0.096
	(0.105)	(0.233)	(0.198)
N	477	477	477
Countries	12	12	12
Sum of lags	0.655	0.937	0.796
Standard error	0.239	0.554	0.241
p-value	0.006	0.091	0.001

Notes: This table presents the average marginal effects (AME) from estimates in Column (9) of Table 4, with five lags of each variable shown in separate columns. Column (1) reports the AME for the change in the loans-to-GDP ratio, column (2) for the change in log private wealth-income ratio, and column (3) for the change in the wealth share of the top 1%. The sum of the lags, along with its standard error and p-value, is also reported. Country-clustered robust standard errors are shown in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.
Source: Own estimations using data from the Macrohistory Database and WID.

Alternative chronologies of financial crises. It is important to note that defining and coding the precise year of a financial crisis episode involves a certain degree of subjectivity. Baron et al. (2021) highlight that the narrative approach to identifying banking crises is based on salient characteristics but lacks a strict quantitative definition, which has led to disagreements among researchers who have developed different chronologies of financial crises. To address this, they first compile what they term "Narrative Crises," by harmonizing dates of episodes of financial crises from six influential studies: Bordo et al. (2001), Caprio and Klingebiel (2002), Demirgüç-Kunt and Detragiache (2005), Laeven and Valencia (2013), Reinhart and Rogoff (2009), and Schularick and Taylor (2012)[13]. Then they introduce a new list, blending the narrative approach—which includes "widespread panic" as a key criterion—with a quantitative measure, using a 30% cumulative decline in bank equity as a threshold.

[13] The list provided by Schularick and Taylor (2012) is updated by Jordà et al. (2017), which we use for our main analysis.

Figure 5: Classification of financial crises from Table 4



Notes: This figure shows the area under the receiver operating characteristic curve (AUC) for the models presented in Table 4. AUC values are reported for three models: column (2), which includes growth in loans-to-GDP ratio and country fixed effects; column (8), which adds the growth in the private wealth-income ratio and top 1% wealth share; and column (9), which includes additional controls. *Source*: Own estimations using data from the Macrohistory Database and WID.

Thus, in addition to using the financial crisis list from Jordà et al. (2017), we conduct robustness checks with alternative chronologies of financial crises. Table 6 presents these results.[14] For ease of comparison with our main results, columns (1) and (2) use the financial crisis episodes as defined by Jordà et al. (2017), hereafter referred to as JST, which correspond to the results in columns (8) and (9) of Table 2.

In columns (3) and (4), we apply the systemic banking crisis definition from Reinhart and Rogoff (2009), abbreviated as RR. Columns (5) and (6) use the new list from Baron et al. (2021), denoted by BVX, and columns (7) and (8) employ the "Narrative Crises" list from the same source, abbreviated as BVXN. In all odd-numbered columns, we include the growth in real loans, W/Y, the top 1% wealth share, and country fixed effects. In all even-numbered columns, we incorporate the full set of controls from our final model in Table 2.

[14]Table A.1 presents the corresponding results, where credit growth is defined as growth in the loans-to-GDP ratio rather than in real loans.

Table 6: Wealth concentration and alternative chronologies of crises

	JST		RR		BVX		BVXN	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ log real Loans$_{t-1}$	12.617**	32.242***	7.024**	14.756***	3.794	-3.470	6.742	8.824*
	(4.911)	(11.420)	(3.409)	(4.636)	(3.295)	(5.945)	(4.348)	(4.740)
Δ log real Loans$_{t-2}$	7.402	-0.759	6.587**	-2.586	0.196	-5.156	11.988**	8.831**
	(6.585)	(7.313)	(2.696)	(4.580)	(5.525)	(5.968)	(4.756)	(3.691)
Δ log real Loans$_{t-3}$	-0.381	12.563	-0.728	1.457	1.524	4.991	-1.739	-0.608
	(6.593)	(7.937)	(4.035)	(5.120)	(5.232)	(4.664)	(4.601)	(3.793)
Δ log real Loans$_{t-4}$	4.460	-12.109	-3.762	-8.125*	-1.544	0.107	-4.732	-5.781
	(8.969)	(13.468)	(3.664)	(4.215)	(4.074)	(4.705)	(3.434)	(3.907)
Δ log real Loans$_{t-5}$	0.287	0.396	2.735	5.462	4.281	6.204	3.973	4.840
	(6.676)	(6.528)	(2.994)	(3.508)	(2.612)	(4.305)	(3.546)	(4.230)
Δ log (W/Y)$_{t-1}$	-10.921**	-19.797***	2.309	2.427	-7.538*	-12.812*	-2.145	-6.205
	(5.288)	(6.774)	(5.034)	(4.991)	(4.119)	(7.327)	(5.039)	(4.232)
Δ log (W/Y)$_{t-2}$	11.892	19.889	4.156	5.456	5.524	4.503	3.735	6.366
	(11.438)	(13.878)	(6.337)	(5.225)	(6.081)	(6.367)	(6.155)	(5.774)
Δ log (W/Y)$_{t-3}$	11.758**	23.409***	1.408	2.804	7.030***	11.315***	0.554	-0.481
	(4.948)	(7.668)	(3.976)	(9.129)	(2.113)	(3.582)	(4.986)	(7.510)
Δ log (W/Y)$_{t-4}$	12.054**	39.282***	10.719*	20.725***	5.938	9.506	17.187***	24.750***
	(5.250)	(10.273)	(5.499)	(7.823)	(4.306)	(5.872)	(5.431)	(7.431)
Δ log (W/Y)$_{t-5}$	-4.119	-12.951	-0.918	-2.479	1.157	1.153	-2.473	-4.240
	(5.063)	(10.282)	(3.040)	(5.225)	(3.263)	(3.209)	(3.660)	(4.526)
Δ log Top 1%$_{t-1}$	7.390***	4.603	6.392	0.830	6.886	5.989	4.846	1.818
	(2.855)	(5.142)	(3.922)	(7.312)	(4.497)	(5.199)	(4.091)	(5.769)
Δ log Top 1%$_{t-2}$	24.293***	42.433***	16.945*	19.955***	10.084*	10.864*	20.773**	22.453***
	(8.424)	(14.211)	(8.675)	(7.209)	(5.319)	(5.976)	(9.226)	(8.313)
Δ log Top 1%$_{t-3}$	0.970	-1.385	-0.735	-2.879	2.366	1.794	3.043	2.767
	(5.318)	(6.324)	(3.518)	(5.455)	(3.418)	(4.561)	(3.695)	(4.606)
Δ log Top 1%$_{t-4}$	6.381	-1.003	4.764	0.376	8.114*	7.676*	3.597	1.219
	(8.009)	(12.517)	(7.293)	(6.337)	(4.758)	(4.172)	(6.479)	(5.620)
Δ log Top 1%$_{t-5}$	-0.302	-1.168	-0.086	-1.029	4.790	6.246	-0.143	-1.429
	(4.908)	(9.380)	(4.464)	(4.063)	(3.140)	(3.976)	(5.211)	(4.555)
Joint sign. of lags, χ^2:								
Δ log real Loans	1.263	11.861	5.971	17.813	0.001	8.119	6.352	31.973
p-value	0.261	0.037	0.015	0.003	0.972	0.150	0.012	0.000
Δ log (W/Y)	48.051	25.154	6.974	31.441	19.601	15.608	25.898	19.285
p-value	0.000	0.000	0.223	0.000	0.001	0.008	0.000	0.002
Δ log Top 1%	30.054	67.510	19.590	169.432	17.507	30.403	34.361	81.647
p-value	0.000	0.000	0.001	0.000	0.004	0.000	0.000	0.000
N	550	481	400	365	530	489	498	457
Countries	13	12	11	10	15	14	13	12
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R^2	0.294	0.517	0.167	0.335	0.143	0.243	0.211	0.297
Pseudolikelihood	-58.295	-35.491	-70.994	-51.575	-108.193	-87.435	-78.259	-64.100
AUC	0.901	0.961	0.800	0.885	0.791	0.841	0.850	0.874
Standard error	0.026	0.015	0.048	0.039	0.036	0.036	0.036	0.040

Notes: This table presents the results from logit models for systemic banking crises, emphasizing wealth inequality as the main variable of interest, along with other key factors. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). The dependent variable is set to 1 in the first year of a financial crisis event and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 2 are included. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, and the test statistics for the joint significance of the lags of the three variables shown in the table, are displayed at the bottom. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Regardless of the crisis chronology used, we consistently find a positive and statistically significant relationship between the growth in wealth inequality and the likelihood of a financial crisis. Table 7 presents the average marginal effects from the final models (even-numbered columns) in Table 6.[15] Columns (1), (4), (7), and (10) display the average marginal effects of the five lags of credit growth, measured by real loans. Columns (2), (5), (8), and (11) show the average marginal effects of the five lags of growth in W/Y. Finally, columns (3), (6), (9), and (12) present the average marginal effects of the five lags of growth in the top 1% wealth share.

Table 7: Average marginal effects for the final models in Table 6

	JST			RR			BVX			BVXN		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$t-1$	0.694***	-0.426***	0.099	0.578***	0.095	0.033	-0.172	-0.634*	0.296	0.339*	-0.239	0.070
	(0.195)	(0.122)	(0.109)	(0.168)	(0.200)	(0.287)	(0.294)	(0.346)	(0.257)	(0.182)	(0.156)	(0.222)
$t-2$	-0.016	0.428	0.913***	-0.101	0.214	0.782***	-0.255	0.223	0.538*	0.340**	0.245	0.864***
	(0.157)	(0.293)	(0.263)	(0.173)	(0.206)	(0.276)	(0.300)	(0.314)	(0.291)	(0.146)	(0.219)	(0.313)
$t-3$	0.270*	0.504***	-0.030	0.057	0.110	-0.113	0.247	0.560***	0.089	-0.023	-0.018	0.106
	(0.151)	(0.135)	(0.134)	(0.198)	(0.353)	(0.211)	(0.232)	(0.180)	(0.225)	(0.146)	(0.290)	(0.178)
$t-4$	-0.261	0.845***	-0.022	-0.319**	0.812***	0.015	0.005	0.470*	0.380*	-0.222	0.952***	0.047
	(0.288)	(0.180)	(0.269)	(0.154)	(0.273)	(0.248)	(0.233)	(0.275)	(0.198)	(0.154)	(0.228)	(0.215)
$t-5$	0.009	-0.279	-0.025	0.214	-0.097	-0.040	0.307	0.057	0.309	0.186	-0.163	-0.055
	(0.141)	(0.211)	(0.201)	(0.137)	(0.202)	(0.162)	(0.212)	(0.160)	(0.192)	(0.168)	(0.169)	(0.178)
N	481	481	481	365	365	365	489	489	489	457	457	457
Countries	12	12	12	10	10	10	14	14	14	12	12	12
Sum of lags	0.696	1.072	0.936	0.430	1.134	0.676	0.132	0.676	1.612	0.619	0.776	1.032
Standard error	0.271	0.526	0.244	0.301	0.657	0.258	0.306	0.526	0.547	0.219	0.608	0.368
p-value	0.010	0.041	0.000	0.153	0.084	0.009	0.665	0.199	0.003	0.005	0.201	0.005

Notes: This table presents the average marginal effects (AME) from estimates in even-numbered columns of Table 6, with five lags of each variable shown in separate columns. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). Column (1) reports the AME for the change in log real loans, column (2) for the change in log private wealth-income ratio, and column (3) for the change in the wealth share of the top 1%. The sum of the lags, along with its standard error and p-value, is also reported. Country-clustered robust standard errors are shown in parentheses. *p <0.10, **p <0.05, ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

While the relationships between credit growth, or growth in W/Y, and financial crises become statistically insignificant in some specifications, the key relationship—between wealth inequality and various definitions of financial crises—remains robust. Regardless of the chronology of financial crises we use, this relationship holds. In our preferred specification using the financial crises list from JST, we find that, when holding all else constant, a one standard deviation rise in the growth of the share of wealth held by the top 1% is associated

[15] Table A.2 presents the average marginal effects from the final models (even-numbered columns) in Table A.1.

with a 4.5 pp increase in the likelihood of a systemic banking crisis. When we use the definition from RR, this coefficient decreases to 3.4 pp. When we use the new list of BVX, the coefficient increases to 7.6 pp, while with the harmonized "Narrative list" from BVX, the coefficient is 5 pp. Thus, depending on the financial crisis chronology examined, we find that, all else equal, a one standard deviation increase in the growth of the top 1% wealth share is associated with an increase in the probability of financial crises ranging from approximately 3 to 8 pp. In all cases, this relationship is statistically significant at the 1% level.

Figure 6 displays the AUC statistic for each final model using alternative chronologies of financial crises.[16] Although our preferred specification yields the highest AUC, all other specifications also surpass the baseline model from Schularick and Taylor (2012). Their replicated baseline model has an AUC of approximately 0.71, whereas the lowest AUC in our analysis is around 0.84, observed in the model employing the new crisis chronologies from BVX. This reinforces the predictive power of our model in all lists of crises used.

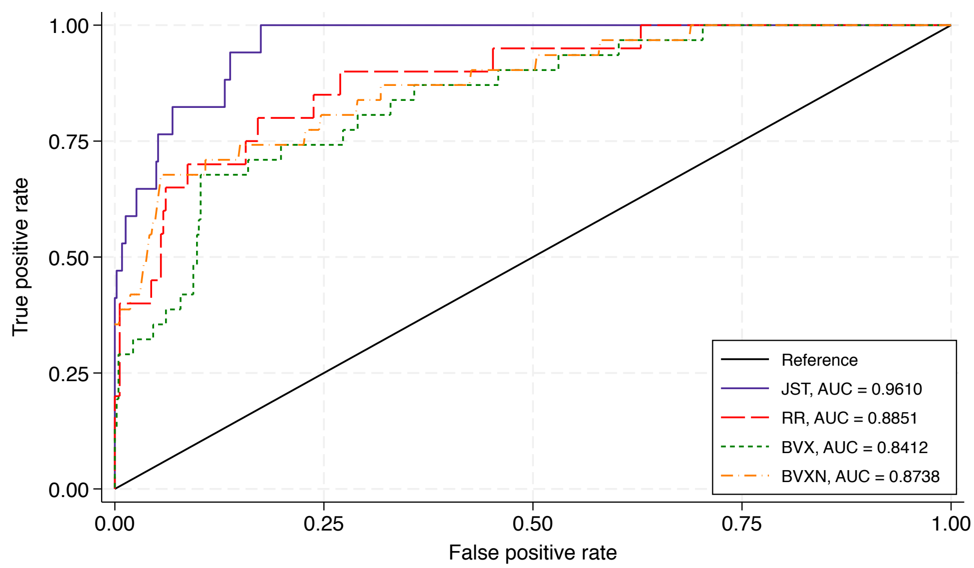
Sample restriction to specific time periods. Because one-third of countries in our final model have data on wealth inequality dating back to the late 19$^{\text{th}}$ century, we are able to restrict our sample to different time periods to test the robustness of our results. Following Schularick and Taylor (2012), we first exclude the periods 1914-1919, corresponding to World War I (WWI), and 1939-1947, corresponding to World War II (WWII) and the immediate post-war years, thus restricting the sample to peacetime. Table A.4 presents the results for this sample, while Table A.5 shows the corresponding average marginal effects. Since wealth inequality data is missing for many countries during the World Wars, the resulting sample in peacetime is similar to the one used for our main results. Once again, irrespective of the crises chronology used, the relationship between the growth in wealth inequality and financial crises remains positive and highly significant.

Next, we restrict the sample to the post-WWII period, from 1946 to 2020. Table 8 presents the results and Table 9 shows the corresponding average marginal effects for the

[16]Figure A.1 shows the AUC statistics for the final models (even-numbered) in Table A.1.

final model. Except when using the new list of systemic banking crises from BVX, the relationship between wealth accumulation growth and financial crises remains positive and statistically significant. Holding all other covariates constant, a one standard deviation increase in the growth of W/Y is associated with an increase in the likelihood of a systemic banking crisis by 14.9 pp for JST, significant at the 10% level, 10.8 pp for RR, significant at the 1% level, or 6.4 pp for BVXN, significant at the 10% level. Thus, in the post-WWII period, the growth in private wealth accumulation is linked to a 6 to 15 pp increase in the probability of financial crises, depending on the list of crises used.

Figure 6: Classification of financial crises from Table 6



Notes: This figure shows the area under the receiver operating characteristic curve (AUC) for the models presented in Table 6. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). It compares AUC values across four models from Table 6: column (2), which uses the financial crises chronology from Jordà et al. (2017); column (4), which applies the systemic banking crises list from Reinhart and Rogoff (2009); column (6), which employs the new crisis list from Baron et al. (2021); and column (8), which utilizes the narrative-based crisis list from Baron et al. (2021). *Source*: Own estimations using data from the Macrohistory Database and WID.

Table 8: Wealth concentration and financial crises in the post-WWII period

	JST		RR		BVX		BVXN	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ log real Loans$_{t-1}$	18.123***	106.014*	6.103	8.746	7.627*	-1.333	10.288**	10.777**
	(5.824)	(55.933)	(6.371)	(10.728)	(4.048)	(8.850)	(5.220)	(5.179)
Δ log real Loans$_{t-2}$	-6.559	-29.570	2.079	-1.881	-9.795**	-12.471	2.399	3.085
	(6.284)	(19.932)	(4.848)	(11.350)	(4.611)	(9.510)	(4.256)	(5.001)
Δ log real Loans$_{t-3}$	5.088	63.634*	3.329	-5.985	8.302	7.372	4.634	2.309
	(5.214)	(34.241)	(6.788)	(11.246)	(5.744)	(6.904)	(5.767)	(7.212)
Δ log real Loans$_{t-4}$	5.680	-75.285	-17.133	-20.510*	-4.042	2.372	-9.751	-4.224
	(7.677)	(46.987)	(11.020)	(11.644)	(5.456)	(7.516)	(6.334)	(5.752)
Δ log real Loans$_{t-5}$	-3.951	0.560	7.011	9.348	2.855	1.299	5.051	1.119
	(7.319)	(18.681)	(7.320)	(12.233)	(4.101)	(5.947)	(4.639)	(5.420)
Δ log (W/Y)$_{t-1}$	-15.865**	-68.963**	-8.431	-10.593	-8.203	-18.246**	-8.336	-6.958
	(7.826)	(32.148)	(7.682)	(12.297)	(7.030)	(8.661)	(8.115)	(10.059)
Δ log (W/Y)$_{t-2}$	18.910	105.085**	18.196	39.805**	10.929**	7.132	11.802	16.310
	(13.776)	(45.374)	(14.865)	(19.287)	(4.569)	(5.484)	(8.886)	(10.093)
Δ log (W/Y)$_{t-3}$	16.007	119.913	2.714	-5.060	9.928**	17.553***	5.565	9.310
	(12.864)	(77.865)	(10.982)	(16.164)	(4.722)	(5.652)	(8.096)	(7.978)
Δ log (W/Y)$_{t-4}$	18.361**	113.919*	27.571***	65.542***	8.131	12.153	18.943**	31.211**
	(8.694)	(68.953)	(10.661)	(16.050)	(6.110)	(7.413)	(8.263)	(14.060)
Δ log (W/Y)$_{t-5}$	-8.210	-64.334**	-4.303	-14.937	1.247	3.446	-3.102	-6.666
	(7.469)	(27.338)	(4.363)	(12.694)	(4.183)	(5.027)	(3.883)	(8.350)
Δ log Top 1%$_{t-1}$	6.970**	-6.394	9.720***	7.291	8.291	6.481	5.687	2.044
	(3.357)	(19.731)	(3.487)	(6.385)	(6.414)	(8.109)	(3.875)	(7.073)
Δ log Top 1%$_{t-2}$	25.829***	106.222**	19.557*	26.369**	9.347*	10.814	19.520**	20.641***
	(9.830)	(48.151)	(10.544)	(12.196)	(5.544)	(7.313)	(9.122)	(8.006)
Δ log Top 1%$_{t-3}$	5.523	15.883	3.878	0.064	3.762	2.103	5.057	3.447
	(4.887)	(21.187)	(4.348)	(4.437)	(3.547)	(4.788)	(3.726)	(3.291)
Δ log Top 1%$_{t-4}$	2.797	-15.183	2.080	-6.447	7.178	7.115	2.104	-2.651
	(8.148)	(14.723)	(7.875)	(9.097)	(4.878)	(6.145)	(6.341)	(5.644)
Δ log Top 1%$_{t-5}$	-1.306	16.349	-6.705	-18.632**	2.786	5.129	-3.645	-4.402
	(5.037)	(12.146)	(6.430)	(7.744)	(3.720)	(5.257)	(5.172)	(6.265)
Joint sign. of lags, χ^2:								
Δ log real Loans	1.089	9.732	0.184	28.822	4.512	3.400	0.318	5.846
p-value	0.297	0.083	0.668	0.000	0.034	0.639	0.573	0.321
Δ log (W/Y)	18.590	8.750	42.004	85.675	17.609	24.418	22.093	16.743
p-value	0.002	0.119	0.000	0.000	0.003	0.000	0.001	0.005
Δ log Top 1%	16.461	15.031	17.942	22.012	13.013	11.293	35.113	27.561
p-value	0.006	0.010	0.003	0.001	0.023	0.046	0.000	0.000
N	442	398	292	282	422	406	390	374
Countries	13	12	11	10	15	14	13	12
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R^2	0.324	0.661	0.250	0.470	0.165	0.266	0.228	0.366
Pseudolikelihood	-48.728	-22.734	-50.691	-34.011	-86.052	-70.862	-63.137	-49.493
AUC	0.904	0.985	0.848	0.946	0.805	0.867	0.854	0.909
Standard error	0.029	0.007	0.048	0.023	0.034	0.031	0.043	0.036

Notes: This table presents the results from logit models for different chronologies of systemic banking crises in the post-1945 period. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). The dependent variable is set to 1 in the first year of a financial crisis event and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 2 are included. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, and the test statistics for the joint significance of the lags of the three variables shown in the table, are displayed at the bottom. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01.
Source: Own estimations using data from the Macrohistory Database and WID.

Moreover, except when using the systemic banking crises list from RR, which yields the smallest sample and fewest countries, the relationship between the growth in wealth inequality and financial crises remains positive and statistically significant. Specifically, all else equal, a one standard deviation increase in the growth of the top 1% wealth share is associated with a higher likelihood of a financial crisis by 10.5 pp for JST, significant at the 10% level, 7.4 pp for BVX, significant at the 5% level, and 3.5 pp for BVXN, significant at the 10% level. Thus, in the post-WWII period, the growth in top 1% wealth concentration is associated with a 4 to 11 pp increase in the probability of financial crises, depending on the list of crises used.

Table 9: Average marginal effects for the final models in Table 8

	JST			RR			BVX			BVXN		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$t-1$	1.959***	-1.275***	-0.118	0.314	-0.381	0.262	-0.065	-0.895**	0.318	0.400**	-0.258	0.076
	(0.725)	(0.393)	(0.372)	(0.373)	(0.410)	(0.244)	(0.435)	(0.421)	(0.401)	(0.196)	(0.371)	(0.264)
$t-2$	-0.547*	1.942***	1.963***	-0.068	1.430**	0.948**	-0.612	0.350	0.531	0.114	0.605*	0.766***
	(0.301)	(0.588)	(0.585)	(0.406)	(0.648)	(0.401)	(0.456)	(0.269)	(0.352)	(0.188)	(0.362)	(0.289)
$t-3$	1.176**	2.216*	0.294	-0.215	-0.182	0.002	0.362	0.861***	0.103	0.086	0.346	0.128
	(0.459)	(1.147)	(0.345)	(0.421)	(0.576)	(0.159)	(0.334)	(0.279)	(0.234)	(0.266)	(0.292)	(0.120)
$t-4$	-1.392**	2.106**	-0.281	-0.737*	2.355***	-0.232	0.116	0.596*	0.349	-0.157	1.158***	-0.098
	(0.702)	(0.971)	(0.250)	(0.412)	(0.559)	(0.329)	(0.367)	(0.358)	(0.304)	(0.220)	(0.449)	(0.209)
$t-5$	0.010	-1.189***	0.302	0.336	-0.537	-0.670**	0.064	0.169	0.252	0.042	-0.247	-0.163
	(0.344)	(0.397)	(0.187)	(0.452)	(0.426)	(0.275)	(0.293)	(0.248)	(0.254)	(0.204)	(0.298)	(0.240)
N	398	398	398	282	282	282	406	406	406	374	374	374
Countries	12	12	12	10	10	10	14	14	14	12	12	12
Sum of lags	1.208	3.801	2.160	-0.369	2.686	0.311	-0.136	1.081	1.553	0.485	1.603	0.708
Standard error	0.568	2.005	1.176	0.353	0.880	0.371	0.347	0.685	0.715	0.321	0.828	0.392
p-value	0.033	0.058	0.066	0.296	0.002	0.402	0.696	0.114	0.030	0.131	0.053	0.071

Notes: This table presents the average marginal effects (AME) from estimates in even-numbered columns of Table 8, with the five lags of each variable arranged into separate columns. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). Column (1) reports the AME for the change in log real loans, column (2) for the change in log private wealth-income ratio, and column (3) for the change in the wealth share of the top 1%. The sum of the lags, along with its standard error and p-value, is also reported. Country-clustered robust standard errors are shown in parentheses. *p <0.10, **p <0.05, ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Alternative empirical strategy. The main results are further validated through impulse response functions estimated using LP as developed by Jordà (2005). In addition to employing a logit model with country fixed effects, we test robustness using an LPM with country fixed effects. Furthermore, as specified in Equation 2, we estimate a two-way fixed effects LPM that incorporates year fixed effects. Figure 7 illustrates the results of a 1% shock to the growth of W/Y. Panel A displays results without controls, while Panel B includes fully specified models. Across all specifications, the sign and significance of the main findings remain consistent.

As shown in Panel A, the effect sizes are similar across specifications without controls. Regarding the ease and intuitiveness of interpreting LP results, LPM estimates are preferred over logit estimates (Grimm et al., 2023). When five lags in the growth of W/Y are included, the shock—defined as a 1% increase—represents an average increase of 1% over the past five years.[17] Using the LPM with country fixed effects, we find that a 1% increase in the growth of W/Y elevates the probability of a financial crisis by approximately 16 and 17 pp in the second and third years following the shock, respectively. In the two-way fixed effects LPM, significant results are observed only for the third year, where the probability of a financial crisis increases by around 10 pp. It should be noted that a 1% rise over five years constitutes a substantial shock, as the average growth of W/Y observed in the sample is approximately 0.5% over the five-year period.

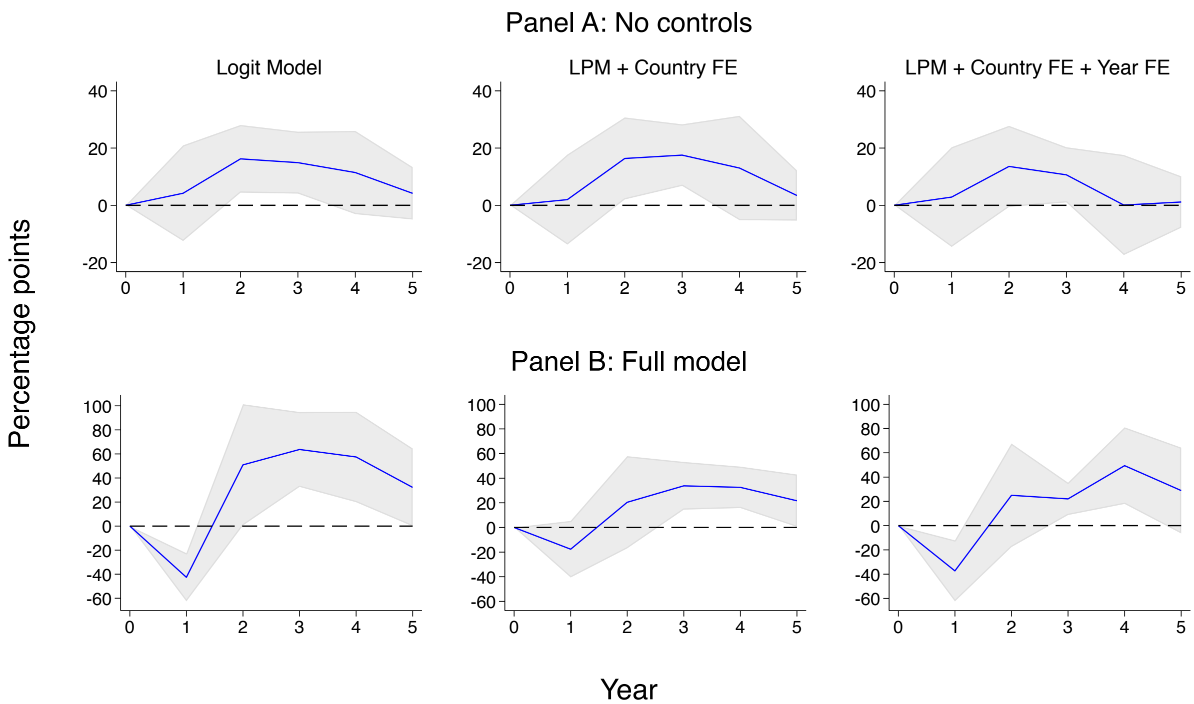
In Panel B, we include all controls as in our full model, including credit growth and the growth in the share of wealth held by the top 1%. Using the LPM with country fixed effects, after controlling for other relevant factors for financial stability, we find that a 1% shock to the growth of W/Y increases the probability of a financial crisis by approximately 34 pp in the third year and 33 pp in the fourth year after the shock. When year fixed effects are also included, we find that such a positive shock initially decreases the probability of a crisis in the following year. This could be due to the short-term effects of wealth accumulation that may boost liquidity in the banking sector. But then it elevates the likelihood of crises by 22 pp and 49 pp in the third and fourth years, respectively. Given that the average W/Y growth over the last five years in this sample is about 1.1%, this represents a realistic shock.

These results are consistent with our main findings in Table 2, where the third and fourth lags of the growth of W/Y are both positive and highly significant. The larger effect sizes in

[17] For brevity, we refer to this shock as a 1% shock, increase or rise.

the two-way fixed effects LPM specification can be attributed to the inclusion of year fixed effects, which account for time-specific macroeconomic shocks and common trends that may otherwise confound the relationship between wealth accumulation and financial crises. It is again confirmed that while a sustained five-year rise in the private wealth accumulation may reduce the likelihood of a financial crisis in the following year, the probability of a crisis increases significantly three to four years afterward.

Figure 7: Financial crisis probability response to a shock to the private wealth-income ratio



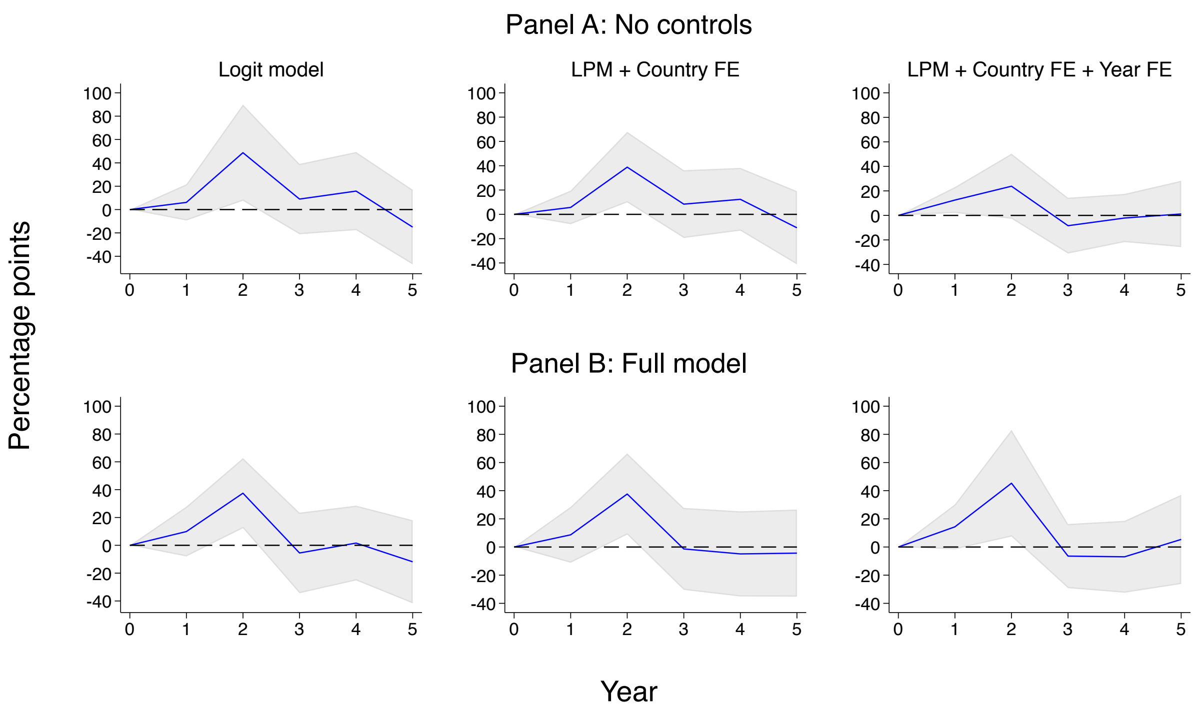
Notes: This figure shows how a 1% average increase over the past five years in the growth of private wealth-income ratio changes the probability of a financial crisis. Results are obtained using local projections (LP) as proposed by Jordà (2005). LP are estimated using a logit model with country fixed effects, a linear probability model (LPM) with country fixed effects, and a two-way fixed effects LPM. Panel A shows results without additional controls, while Panel B includes the full models. In addition to the growth in real loans and the private wealth-income ratio, the same controls as described in Table 2 are included. Five lags of the growth of top 1% wealth share and one lag of each control variable are included. The projection horizon is 5 years. The shaded areas denote the 90% confidence intervals, estimated from country-clustered robust standard errors. *Source*: Own estimations using data from the Macrohistory Database and WID.

Figure 8 presents the results of the same shock to the growth of wealth inequality. Again, Panel A shows the results from specifications without controls. Using the LPM with country fixed effects, we find that a 1% increase in the growth of the share of wealth held by the top 1% increases the probability of a financial crisis by approximately 39 pp two years later.

When year fixed effects are included in addition to country fixed effects, the probability of a financial crisis elevates by about 13 pp one year after the shock.

In Panel B, we include all controls as in the full model. Using the LPM with country fixed effects, and controlling for other factors, a 1% shock to the growth of wealth concentration at the top percentile increases the probability of a financial crisis by approximately 38 pp in the second year following the shock. When year fixed effects are incorporated, this estimate rises to about 45 pp. These findings further corroborate our main results in Table 2, where the second lag of the growth in wealth inequality is both positive and highly significant. In other words, the probability of a financial crisis increases substantially two years following a sustained five-year surge in the growth of wealth concentration at the top of the distribution.

Figure 8: Financial crisis probability response to a shock to wealth inequality



Notes: This figure shows how a 1% average increase over the past five years in the growth of the top 1% wealth share changes the probability of a financial crisis. Results are obtained using local projections (LP) as proposed by Jordà (2005). LP are estimated using a logit model with country fixed effects, a linear probability model (LPM) with country fixed effects, and a two-way fixed effects LPM. Panel A shows results without additional controls, while Panel B includes the full models. In addition to the growth in real loans and the private wealth-income ratio, the same controls as described in Table 2 are included. Five lags of the growth of top 1% wealth share and one lag of each control variable are included. The projection horizon is 5 years. The shaded areas denote the 90% confidence intervals, estimated from country-clustered robust standard errors. *Source*: Own estimations using data from the Macrohistory Database and WID.

5.3 Wealth concentration and asset price bubbles

5.3.1 House price bubbles

To investigate whether asset price bubbles serve as a potential transmission channel through which wealth accumulation and inequality could precipitate financial crises, we estimate the likelihood of such bubbles using the growth of W/Y and the top 1% wealth share as key predictors. Given the availability of data for both house and stock prices, we distinguish between house and equity price bubbles. Table 10 presents results from logit regressions that estimate the probability of a house price bubble, with growth in the accumulation of private wealth and growth in wealth inequality as key explanatory variables. Panel A reports the log-odds coefficients. Panel B provides the corresponding average marginal effects. Because our primary focus is on exploring the role of asset price bubbles as a potential transmitter, we adopt a simplified lag structure, incorporating a one-period lag for each independent variable to maintain clarity and parsimony in the model.

Since credit expansion can drive asset price bubbles, we first assess its role as shown in column (1), which presents results using the growth in real loans, and in column (2), where we add country fixed effects. Similarly, columns (3) and (4) incorporate the growth in W/Y. Columns (5) and (6) use the growth in the top 1% wealth share. Column (7) combines all three variables without country fixed effects, which are controlled for in column (8). In the final model presented in column (9), we control for the growth in real GDP per capita, investment-to-GDP ratio, current account-to-GDP ratio, real broad money, real short-term interest rates, banks' capital ratios, and banks' loans-to-deposits ratios, in addition to country fixed effects.

Our main finding is that credit growth and private wealth accumulation are similarly strong predictors of house price bubbles in terms of the effect size. The average real loan growth in this sample has a standard deviation of approximately 0.06. Holding all other covariates constant, a one standard deviation increase in real loan growth is associated with a 6.2 pp rise in the probability of a house price bubble, which is significant at the 1% level. Similarly, the average growth of W/Y in this sample has a standard deviation of about 0.05. Controlling for other covariates, a one standard deviation increase in W/Y growth is associated with a 6.3 pp rise in the probability of a house price bubble. This relationship is also significant at the 1% level.

Table 10: Wealth concentration and house price bubbles

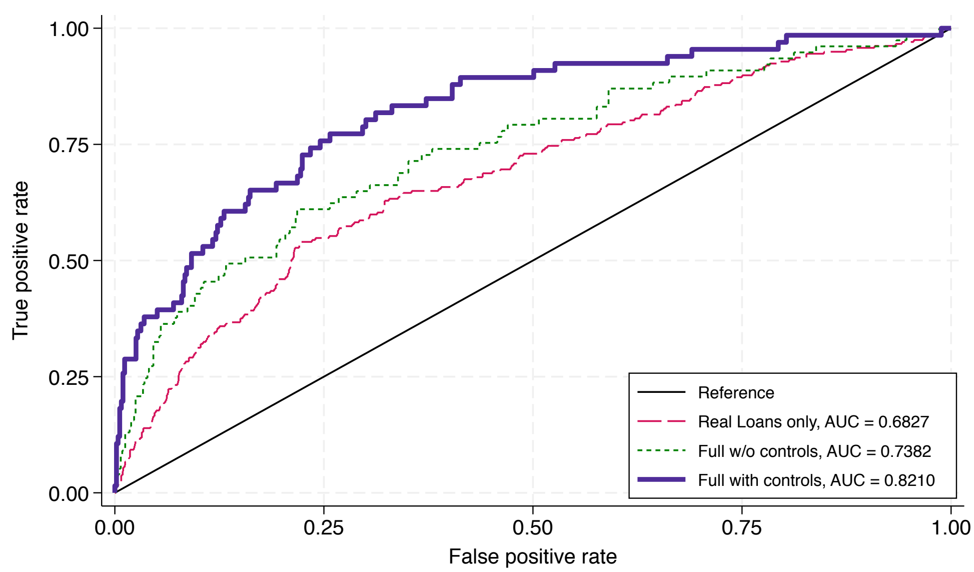
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Panel A: Logit regression coefficients				
Δ log real Loans$_{t-1}$	6.482***	7.020***					8.871*	7.549	12.621***
	(1.930)	(2.129)					(5.301)	(5.286)	(3.893)
Δ log (W/Y)$_{t-1}$			6.380**	6.340**			10.717***	11.366***	15.320***
			(2.772)	(2.812)			(2.606)	(2.463)	(4.272)
Δ log Top 1%$_{t-1}$					-1.377	-0.159	-3.701	-1.953	-0.375
					(1.669)	(1.784)	(2.319)	(2.331)	(3.225)
					Panel B: Average marginal effects				
Δ log real Loans$_{t-1}$	0.669***	0.717***					0.750*	0.723	1.025***
	(0.178)	(0.200)					(0.392)	(0.470)	(0.287)
Δ log (W/Y)$_{t-1}$			0.612**	0.640**			0.907***	1.088***	1.244***
			(0.271)	(0.276)			(0.181)	(0.222)	(0.295)
Δ log Top 1%$_{t-1}$					-0.127	-0.017	-0.313*	-0.187	-0.030
					(0.146)	(0.188)	(0.182)	(0.225)	(0.262)
N	1,942	1,942	1,287	1,190	775	655	759	641	579
Countries	18	18	18	15	18	13	18	13	12
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Controls	No	No	No	No	No	No	No	No	Yes
Pseudo R^2	0.040	0.056	0.019	0.041	0.001	0.028	0.090	0.112	0.216
Pseudolikelihood	-691.334	-679.927	-436.469	-415.431	-257.259	-236.276	-226.759	-209.087	-161.112
AUC	0.657	0.683	0.634	0.667	0.505	0.617	0.722	0.738	0.821
Standard error	0.020	0.019	0.026	0.025	0.035	0.031	0.036	0.033	0.029

Notes: This table presents the results from logit models for house price bubbles, highlighting wealth inequality as the main variable of interest along with other key factors. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. The dependent variable is set to 1 when, in any given country, the log of the real house price rises by more than one standard deviation from its Hodrick–Prescott filtered trend, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. Controls include: the change in (i) real GDP per capita, (ii) investment-to-GDP ratio, (iii) current account-to-GDP ratio, (iv) real broad money, (v) real short-term interest rates, (vi) capital ratio of banks, and (vii) banks' loans-to-deposits ratios. Except for the current account-to-GDP ratio and short-term interest rates, which may contain negative values, all variables are log-transformed. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

We find no evidence of a statistically significant relationship between growth in the share of wealth held by the top 1% and house price bubbles. This lack of significance could be attributed to the composition of this group's portfolio. The latter tends to be more concentrated in financial assets, such as equities, than housing assets (Kuhn et al., 2020). In contrast, housing has historically been the largest component of household wealth for the broader population, and capital gains in housing have been a key driver of the rise in W/Y (Piketty and Zucman, 2014; Grossmann et al., 2024).

To compare the predictive power of the models, we use the AUC statistics. Figure 9 presents the AUC values for various model specifications. In the baseline model, which includes only growth in real loans, the AUC is 0.6827. When measures of wealth accumulation and inequality are incorporated, the AUC increases to 0.7382. Finally, by adding additional control variables, the AUC increases to 0.8210 in the final model, reflecting a notable improvement in predictive accuracy. This progression demonstrates that including wealth variables and controls improves the ability to predict house price bubbles.

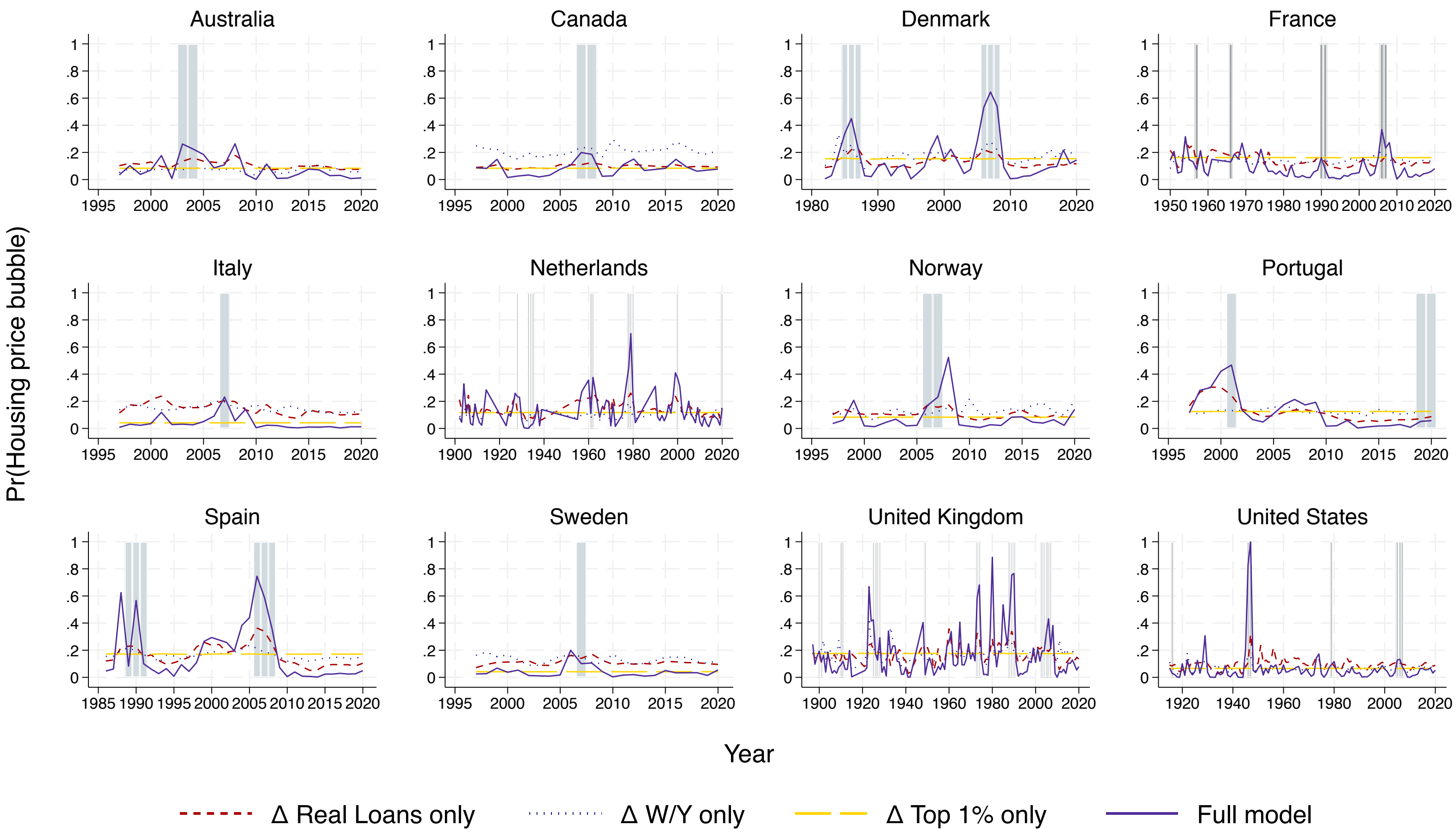
Figure 9: Classification of house price bubbles from Table 10



Note: This figure shows the area under the receiver operating characteristic curve (AUC) for the models presented in Table 10. AUC values are reported for three models: column (2), which includes growth in real loans and country fixed effects; column (8), which adds the growth in the private wealth-income ratio and top 1% wealth share; and column (9), which includes additional controls. *Source*: Own estimations using data from the Macrohistory Database and WID.

Figure 10 presents the predicted probabilities of house price bubbles across countries, as estimated from different model specifications. We compare single-variable models—each emphasizing the growth in real loans, W/Y, or the top 1% wealth share—to the final model. The latter demonstrates superior overall performance, particularly in predicting bubble probabilities during critical periods, although its effectiveness varies by country. For example, the model successfully identifies bubble signals in the years preceding the GFC for Denmark, Spain, the UK, and France. These signals are reflected in the probability spikes observed within and around the shaded areas, which represent empirically identified bubbles. However, its predictive accuracy is less robust for the US and some other countries, highlighting the variability in its applicability in different country contexts.

Figure 10: Predictions of house price bubbles



Note: This figure shows the probabilities of house price bubbles for each country in our final sample, as predicted by different models from Table 10. It compares the in-sample predictions from the model in column (2), which includes growth in real loans and country fixed effects; column (4), which adds growth in the private wealth-income ratio and country fixed effects; column (6), which includes the growth in the share of wealth held by the top 1% along with country fixed effects; and the final model in column (9), which combines all three variables with additional controls and country fixed effects. The shaded areas represent the first year of a financial crisis event, as identified in the Jordà-Schularick-Taylor a financial crisis chronology. *Source*: Own estimations using data from the Macrohistory Database and WID.

5.3.2 Robustness checks of house price bubble results

In line with our analysis of financial crises, we perform several robustness checks to validate our main findings regarding the role of wealth accumulation and inequality in the probability of house price bubbles. Specifically, we explore (i) an alternative definition of credit growth, (ii) an alternative definition of house price bubbles, and (iii) a restricted sample over various time periods. For the first check, instead of using real loans as our measure of credit, we employ the loans-to-GDP ratio. As presented in Table 11, the results indicate that, with only minor variations in magnitude, our findings remain consistent.

Table 11: Wealth concentration, loans-to-GDP ratio, and house price bubbles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Logit regression coefficients								
Δ log (Loans/GDP)$_{t-1}$	6.478***	7.004***					8.221	7.168	11.321***
	(1.692)	(1.901)					(5.817)	(5.378)	(3.618)
Δ log (W/Y)$_{t-1}$			6.380**	6.340**			9.524***	10.236***	15.124***
			(2.772)	(2.812)			(2.457)	(2.229)	(3.935)
Δ log Top 1%$_{t-1}$					-1.377	-0.159	-3.176	-1.581	-0.163
					(1.669)	(1.784)	(2.416)	(2.405)	(2.901)
	Panel B: Average marginal effects								
Δ log (Loans/GDP)$_{t-1}$	0.675***	0.722***					0.713	0.702	0.932***
	(0.164)	(0.183)					(0.469)	(0.498)	(0.275)
Δ log (W/Y)$_{t-1}$			0.612**	0.640**			0.826***	1.003***	1.245***
			(0.271)	(0.276)			(0.195)	(0.215)	(0.278)
Δ log Top 1%$_{t-1}$					-0.127	-0.017	-0.275	-0.155	-0.013
					(0.146)	(0.188)	(0.203)	(0.237)	(0.239)
N	1,919	1,919	1,287	1,190	775	655	751	633	579
Countries	18	18	18	15	18	13	18	13	12
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Controls	No	No	No	No	No	No	No	No	Yes
Pseudo R^2	0.034	0.049	0.019	0.041	0.001	0.028	0.073	0.101	0.207
Pseudolikelihood	-689.143	-678.422	-436.469	-415.431	-257.259	-236.276	-230.173	-210.592	-162.866
AUC	0.639	0.664	0.634	0.667	0.505	0.617	0.697	0.725	0.813
Standard error	0.020	0.019	0.026	0.025	0.035	0.031	0.035	0.033	0.029

Notes: This table presents the results from logit models for house price bubbles, highlighting wealth inequality as the main variable of interest along with other key factors. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. The dependent variable is set to 1 when, in any given country, the log of the real house price rises by more than one standard deviation from its Hodrick–Prescott filtered trend, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 10 are included. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

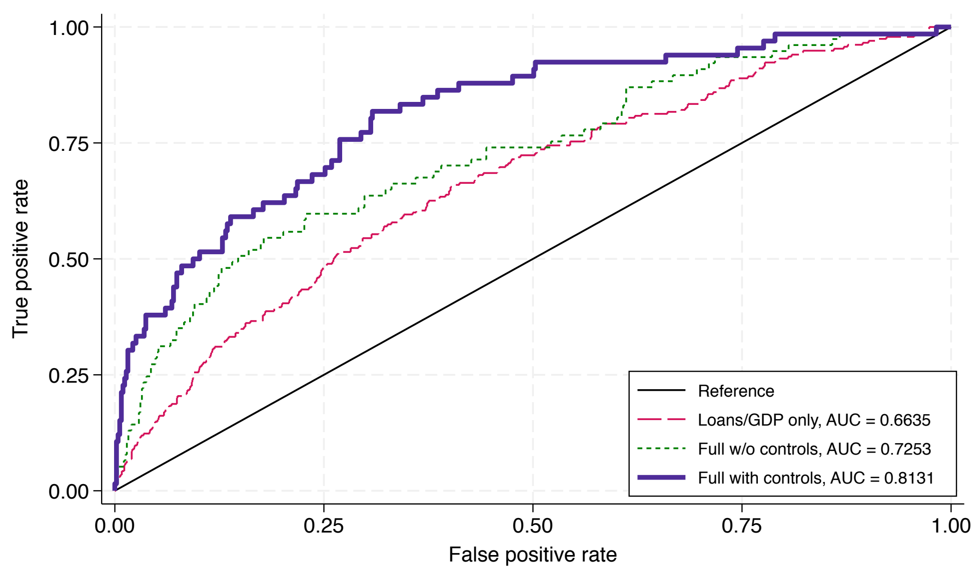
The average growth of the loans-to-GDP ratio in this sample has a standard deviation of approximately 0.058. Holding all other covariates constant, a one standard deviation increase in the growth of loans-to-GDP ratio is associated with a 5.4 pp increase in the probability of a house price bubble. This relationship is significant at the 1% level. Compared to the model using real loans as the measure of credit, this effect is 0.8 pp smaller in magnitude. Furthermore, the corresponding result for W/Y growth is 6.3 pp, which matches the effect size found in the main analysis. This relationship is also significant at the 1% level. Consistent with previous results, we find no statistically significant relationship between the growth of the top 1% wealth share and the occurrence of house price bubbles.

Moreover, Figure 11 presents the AUC values from different models. The final model achieves an AUC of approximately 0.813, outperforming the baseline model that uses only the growth in the loans-to-GDP ratio. However, it is slightly lower than the AUC of 0.821 observed in the final model, where credit is measured in terms of real loans. Nevertheless, irrespective of how credit growth is defined, the results consistently reveal a positive and highly significant relationship between wealth accumulation and the likelihood of house price bubbles.

In the main analysis, we define a house price bubble as the year when the log real house price increase exceeds one standard deviation from its Hodrick-Prescott filtered trend. Although this definition is widely used, there is no universally accepted method in the literature for empirically identifying asset price bubbles. Jordà et al. (2015b) propose an alternative approach that incorporates both a "price elevation" and a subsequent "price correction." Specifically, they define a bubble not only by a price increase exceeding one standard deviation, but also by a price decline of at least 15% within a three-year window following the initial surge. To further assess the robustness of our findings, we adopt this alternative definition.

Table 12 shows our findings using the definition of a house price bubble proposed by Jordà et al. (2015b). Consistent with the main analysis, we find that credit growth significantly increases the likelihood of house price bubbles. Holding all other covariates constant, a one standard deviation rise in real loan growth is associated with a 4.4 pp increase in the probability of a house price bubble. This relationship is significant at the 5% level. Notably, the main difference from the previous findings is that, in the final empirical model presented in Panel B, the coefficient of growth in W/Y becomes statistically insignificant, while the coefficient of the share of wealth held by the top 1% turns significant. All else equal, a one standard deviation increase in the growth of the top 1% wealth share is associated with a 1.7 pp rise in the probability of a house price bubble, with this association also being significant at the 5% level.

Figure 11: Classification of house price bubbles from Table 11



Notes: This figure shows the area under the receiver operating characteristic curve (AUC) for the models presented in Table 11. AUC values are reported for three models: column (2), which includes growth in the loans-to-GDP ratio and country fixed effects; column (8), which adds the growth in the private wealth-income ratio and top 1% wealth share; and column (9), which includes additional controls. *Source*: Own estimations using data from the Macrohistory Database and WID.

One potential explanation for the difference in our results is the number of house price bubble episodes included in each analysis. In our main analysis, the final model covers 66 episodes. In contrast, using the alternative definition proposed by Jordà et al. (2015b) reduces the number of episodes to only 28. This reduction also results in a decrease in the number of countries analyzed, from 12 to 5, which include Denmark, the Netherlands, Spain, the UK and the US. Furthermore, the data on wealth inequality in these countries covers a longer period—several decades for Denmark and Spain, and more than a century for the Netherlands, the UK, and the US.

Table 12: Wealth concentration and an alternative definition of house price bubbles

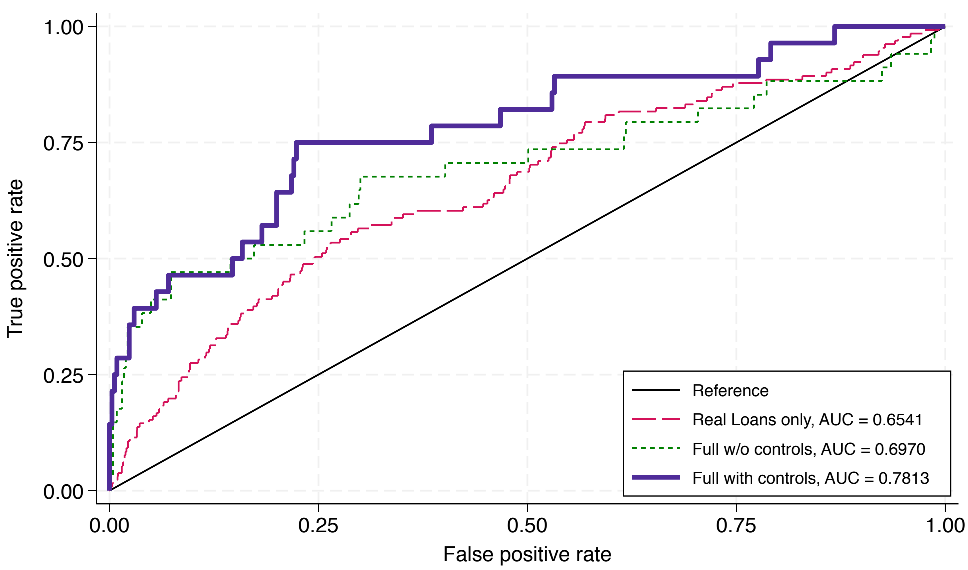
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Logit regression coefficients								
Δ log real Loans$_{t-1}$	4.199**	4.490**					7.063	5.874	11.316**
	(1.746)	(1.917)					(6.047)	(6.897)	(5.525)
Δ log (W/Y)$_{t-1}$			3.818**	3.561**			5.215	5.525*	7.325*
			(1.888)	(1.735)			(3.735)	(3.150)	(4.410)
Δ log Top 1%$_{t-1}$					5.889**	5.467***	4.035	3.760*	5.270**
					(2.571)	(1.800)	(2.937)	(1.939)	(2.365)
	Panel B: Average marginal effects								
Δ log real Loans$_{t-1}$	0.261**	0.281**					0.297	0.358	0.687**
	(0.105)	(0.117)					(0.275)	(0.407)	(0.286)
Δ log (W/Y)$_{t-1}$			0.201*	0.213**			0.219	0.337*	0.445
			(0.104)	(0.102)			(0.157)	(0.189)	(0.274)
Δ log Top 1%$_{t-1}$					0.267**	0.360***	0.169	0.229**	0.320**
					(0.111)	(0.117)	(0.118)	(0.115)	(0.137)
N	1,942	1,909	1,287	1,106	775	511	759	497	368
Countries	18	17	18	13	18	7	18	7	5
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Controls	No	No	No	No	No	No	No	No	Yes
Pseudo R^2	0.017	0.036	0.008	0.029	0.007	0.035	0.042	0.076	0.183
Pseudolikelihood	-471.524	-460.029	-275.424	-258.675	-147.572	-128.087	-132.991	-114.584	-80.884
AUC	0.602	0.654	0.596	0.628	0.582	0.644	0.663	0.697	0.781
Standard error	0.029	0.026	0.037	0.035	0.051	0.043	0.062	0.059	0.051

Notes: This table presents the results from logit models for house price bubbles, highlighting wealth inequality as the main variable of interest along with other key factors. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. Following Jordà et al. (2015b), the dependent variable is set to 1 when, in any given country, (1) the log of the real house price rises by more than one standard deviation from its Hodrick–Prescott filtered trend and (2) the price declines by at least 15% within a three-year window following the price increase, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 10 are included. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Another contributing factor may lie in the definition of credit. As shown in Table A.9, when credit is defined as the loans-to-GDP ratio rather than real loans, a one standard deviation rise in the growth of W/Y corresponds to a 2.4 pp increase in the likelihood of a house price bubble, all else equal. However, this relationship is statistically significant only at the 10% level. In summary, the findings indicate that growth in private wealth accumulation is a strong predictor of house price bubbles across a broader set of countries. In contrast, the growth in wealth inequality is significant only in a narrower sample with longer-term wealth inequality data.

We again use the AUC as a goodness-of-fit statistic. Figure 12 presents the AUC values for different empirical models from Table 12.[18] In the baseline model, which includes only the growth in real loans, the AUC is 0.6541. When we add the growth in W/Y and the share of wealth held by the top 1%, the AUC increases to 0.697. The final model, which incorporates all controls, achieves an AUC of 0.7813, demonstrating enhanced predictive power compared to the previous models. However, this is slightly lower than the AUC of 0.8131 in the main analysis, where a different definition of house price bubbles is used.

Figure 12: Classification of house price bubbles from Table 12



Notes: This figure shows the area under the receiver operating characteristic curve (AUC) for the models presented in Table 12. AUC values are reported for three models: column (2), which includes growth in real loans and country fixed effects; column (8), which adds the growth in the private wealth-income ratio and top 1% wealth share; and column (9), which includes additional controls. *Source*: Own estimations using data from the Macrohistory Database and WID.

[18]Figure A.2 presents the AUC statistics for the corresponding models in Table A.9.

Finally, we restrict the sample to different time periods. Table A.10 presents the results from the analysis excluding WWI and WWII.[19] Columns (1) to (5) show the results using our primary definition of house price bubbles, based on years where the log real house price rises by more than one standard deviation from its Hodrick–Prescott filtered trend. Columns (6) to (10) present results using the alternative definition, as proposed by Jordà et al. (2015b).

The results align with our main findings. Using the main definition of house price bubbles, we observe a positive and highly significant relationship between the growth in private wealth accumulation and the occurrence of house price bubbles. In contrast, there is no statistically significant relationship between the growth in wealth inequality and house price bubbles. For the alternative definition, the sample size is considerably reduced, making the growth of W/Y insignificant. However, in this case, the relationship between the growth in wealth inequality and house price bubbles is positive and becomes statistically significant.

Furthermore, we restrict our analysis to the post-WWII period, as presented in Table 13.[20] In the final model using the main definition, as shown in column (6), we find that, all else equal, a one standard deviation increase in credit growth is associated with a 6.3 pp rise in the probability of house price bubbles, statistically significant at the 1% level. The corresponding result for the growth of W/Y is an 8 pp increase, also significant at the 1% level. In contrast, no statistically significant relationship is found between the growth in wealth inequality and house price bubbles during the post-WWII period.

The main difference from the earlier results is that, when using the alternative definition of house price bubbles, both the growth in private wealth accumulation and the growth in wealth inequality show a positive and significant relationship with house price bubbles during the post-WWII period. As shown in column (10), during the post-WWII period a one standard deviation rise in credit growth is associated with an 8.2 pp increase in the probability of house price bubbles, holding all other covariates constant. This relationship is

[19] In Table A.11, shows the results of models where credit growth is defined as the growth in loans-to-GDP ratio instead of real loans.

[20] In Table A.12, we use the growth in the loans-to-GDP ratio instead of real loans as a measure of credit growth.

significant at the 1% level. The corresponding magnitudes for the growth in the W/Y and the top 1% wealth share are 4.6 and 2.7 pp, respectively. Both relationships are significant at the 5% level.

Table 13: Wealth concentration and house price bubbles in the post-WWII period

	House bubble: Main definition					House bubble: Alternative definition				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Logit regression coefficients									
Δ log real Loans$_{t-1}$	16.024***			18.849***	15.676***	15.459***			25.041***	36.932***
	(1.535)			(4.990)	(5.834)	(2.258)			(9.603)	(6.597)
Δ log (W/Y)$_{t-1}$		11.047*		20.488***	28.322***		5.353		8.180*	28.773**
		(6.670)		(4.769)	(5.022)		(4.290)		(4.307)	(11.989)
Δ log Top 1%$_{t-1}$			-0.337	-1.344	0.380			7.124***	8.086**	13.581**
			(1.835)	(3.333)	(3.192)			(2.421)	(3.251)	(5.727)
	Panel B: Average marginal effects									
Δ log real Loans$_{t-1}$	1.351***			1.394***	1.074***	0.804***			1.176***	1.322***
	(0.098)			(0.302)	(0.375)	(0.097)			(0.297)	(0.267)
Δ log (W/Y)$_{t-1}$		1.181*		1.515***	1.940***		0.347		0.384*	1.030**
		(0.677)		(0.357)	(0.294)		(0.270)		(0.206)	(0.458)
Δ log Top 1%$_{t-1}$			-0.032	-0.099	0.026			0.436***	0.380*	0.486**
			(0.176)	(0.245)	(0.220)			(0.145)	(0.194)	(0.223)
N	1,165	783	511	509	483	986	624	296	296	272
Countries	17	14	13	13	12	14	11	6	6	5
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	Yes	No	No	No	No	Yes
Pseudo R^2	0.165	0.057	0.023	0.266	0.322	0.141	0.044	0.051	0.330	0.474
Pseudolikelihood	-336.705	-284.024	-172.487	-129.562	-113.243	-194.276	-154.562	-69.447	-49.060	-34.890
AUC	0.797	0.704	0.609	0.849	0.880	0.774	0.670	0.686	0.884	0.947
Standard error	0.019	0.028	0.039	0.027	0.024	0.032	0.044	0.057	0.042	0.018

Notes: This table presents the results from logit models for house price bubbles in the post-1945 period. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. In columns (1) to (5), The dependent variable is set to 1 when, in any given country, the log of the real house price rises by more than one standard deviation from its Hodrick–Prescott filtered trend, and 0 otherwise. In columns (6) to (10), following Jordà et al. (2015b), the dependent variable is set to 1 when, in any given country, (1) the log of the real house price rises by more than one standard deviation from its Hodrick–Prescott filtered trend and (2) the price declines by at least 15% within a three-year window following the price increase, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 10 are included. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

The conflicting findings regarding the relationship between W/Y and house price bubbles during the post-WWII period can be attributed to two main factors. First, these results are based on a smaller sample, which includes 28 house price bubble episodes in five countries: Denmark, the Netherlands, Spain, the UK, and the US. Second, the dynamics of house prices after WWII differed considerably. Knoll et al. (2017) observe a surge in housing prices in many countries during the latter part of the 20th century, primarily attributing it to rising land prices. Grossmann et al. (2024) find that the post-war construction boom, combined with increased demand for residential land, was a major driver of the surge in housing wealth-to-income ratios in several countries.

In summary, the analysis reveals that private wealth accumulation significantly predicts house price bubbles, when bubbles are defined as years when, for each specific country, the log real house price exceeds its Hodrick–Prescott filtered trend by more than one standard deviation. This definition allows for the inclusion of a broader set of countries. However, when house price bubbles are defined according to Jordà et al. (2015b)—covering both "price elevation" and "price correction"—this relationship is statistically significant only during the post-WWII period. In contrast, growth in wealth inequality is a significant predictor of house price bubbles only when defined as in Jordà et al. (2015b), irrespective of the period examined. This relationship persists within a smaller sample of countries where wealth inequality data span substantial periods, ranging from several decades for Denmark and Spain to over a century for the Netherlands, the UK and the United States.

5.3.3 Equity price bubbles

To investigate an additional potential transmission channel through which wealth accumulation and inequality can contribute to financial crises, we estimate the probability of an equity price bubble, using the growth in these two wealth variables as key predictors. Table 14 presents the main results, with Panel A displaying the log odds coefficients and Panel B presenting the corresponding average marginal effects. Table 14 mirrors Table 10, where we estimate the probability of house price bubbles. We begin with individual regressions for each variable—credit growth, W/Y growth, and top 1% wealth share growth—and then proceed by incorporating all variables into the full model.

In the final model, shown in column (9), we analyze 108 episodes of equity price bubbles in 17 countries.[21] Since credit growth is found to be one of the key predictors of equity price bubbles, we use it as a benchmark to compare its effect with our main variables of interest. In this sample, the standard deviation of the average real loan growth is approximately 0.061. This means that, all else equal, a one standard deviation rise in real loan growth corresponds to a 6.9 pp increase in the probability of an equity price bubble, which is significant at the 1% level.

Table 14: Wealth concentration and equity price bubbles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Logit regression coefficients								
Δ log real Loans$_{t-1}$	2.660***	2.800***					10.403***	11.614***	9.774***
	(0.839)	(0.813)					(1.746)	(2.182)	(2.410)
Δ log (W/Y)$_{t-1}$			3.286	3.273			9.214***	9.076***	13.074**
			(2.291)	(2.294)			(2.316)	(2.550)	(5.826)
Δ log Top 1%$_{t-1}$					6.492***	5.737***	5.159***	4.456***	3.440***
					(1.532)	(1.676)	(1.426)	(1.540)	(1.240)
	Panel B: Marginal effects								
Δ log real Loans$_{t-1}$	0.320***	0.336***					1.264***	1.378***	1.132***
	(0.103)	(0.095)					(0.205)	(0.230)	(0.265)
Δ log (W/Y)$_{t-1}$			0.422	0.418			1.119***	1.077***	1.514**
			(0.290)	(0.289)			(0.279)	(0.290)	(0.616)
Δ log Top 1%$_{t-1}$					0.876***	0.763***	0.627***	0.529***	0.398***
					(0.191)	(0.219)	(0.161)	(0.181)	(0.142)
N	2,078	2,078	1,291	1,291	706	706	692	692	654
Countries	17	17	17	17	17	17	17	17	17
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Controls	No	No	No	No	No	No	No	No	Yes
Pseudo R^2	0.012	0.018	0.007	0.014	0.012	0.025	0.102	0.122	0.164
Pseudolikelihood	-839.034	-833.538	-547.868	-543.674	-310.113	-305.821	-273.549	-267.691	-245.094
AUC	0.619	0.615	0.599	0.592	0.607	0.627	0.736	0.761	0.789
Standard error	0.018	0.018	0.022	0.022	0.029	0.028	0.025	0.023	0.023

Notes: This table presents the results from logit models for equity price bubbles, highlighting wealth inequality as the main variable of interest along with other key factors. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. The dependent variable is set to 1 when, in any given country, the log of the real equity price rises by more than one standard deviation from its Hodrick–Prescott filtered trend, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. Controls include: the change in (i) real GDP per capita, (ii) investment-to-GDP ratio, (iii) current account-to-GDP ratio, (iv) real broad money, (v) real short-term interest rates, (vi) capital ratio of banks, and (vii) banks' loans-to-deposits ratios. Except for the current account-to-GDP ratio and short-term interest rates, which may contain negative values, all variables are log-transformed. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

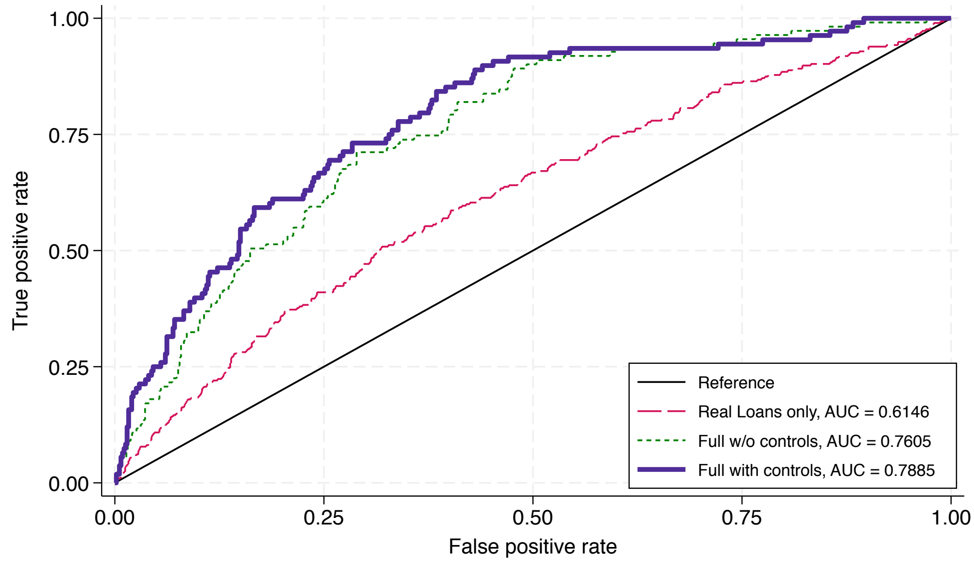
[21] Ireland is excluded due to the unavailability of stock price data.

Our main finding is that growth in private wealth accumulation and inequality are significant predictors of equity price bubbles. However, the growth in W/Y becomes a statistically significant predictor only once we control for the growth in credit and top 1% wealth share. In the final model in column (9), the average growth in W/Y has a standard deviation of about 0.048. Controlling for other determinants of equity price bubbles, a one standard deviation increase in the growth of W/Y corresponds to a 7.3 pp rise in the likelihood of an equity price bubble, which is significant at the 5% level. In the same model, the average growth of the share of wealth held by the top 1% has a standard deviation of about 0.044. This means that, all else equal, a one standard deviation rise in the growth of the top 1% wealth share is associated to a 1.8 pp increase in the likelihood of an equity price bubble, significant at the 1% level.

As shown in Figure 13, we again use the AUC to assess and compare the predictive power of different empirical models. In the baseline model, which includes only growth in real loans, the AUC is 0.6146. When we incorporate our measures of private wealth accumulation and wealth inequality, the AUC rises considerably to 0.7605. Adding other control variables to the final model leads to a marginal enhancement, with the AUC increasing to 0.7885, indicating a slight improvement in predictive precision.

Lastly, Figure 14 illustrates the predicted probabilities of bubbles in equity prices in individual countries based on different model specifications. We compare single-variable models—using growth in real loans, W/Y, or the top 1% wealth share individually— with the full-fledged model. The signals for equity price bubbles are denoted by the probability spikes observed within and around the shaded areas, which represent empirically identified bubble episodes. Although the final model demonstrates overall superior performance, its predictive accuracy varies between bubble episodes and countries. It performs particularly well in identifying bubble signals in Denmark, Italy, the Netherlands, Portugal, Spain, Sweden, the UK and the US. However, its predictive accuracy is less robust for other countries, highlighting the disparities in its effectiveness in different country settings.

Figure 13: Classification of equity price bubbles from Table 14



Notes: This figure shows the area under the receiver operating characteristic curve (AUC) for the models presented in Table 14. AUC values are reported for three models: column (2), which includes growth in real loans and country fixed effects; column (8), which adds the growth in the private wealth-income ratio and top 1% wealth share; and column (9), which includes additional controls. *Source*: Own estimations using data from the Macrohistory Database and WID.

Figure 14: Predictions of equity price bubbles

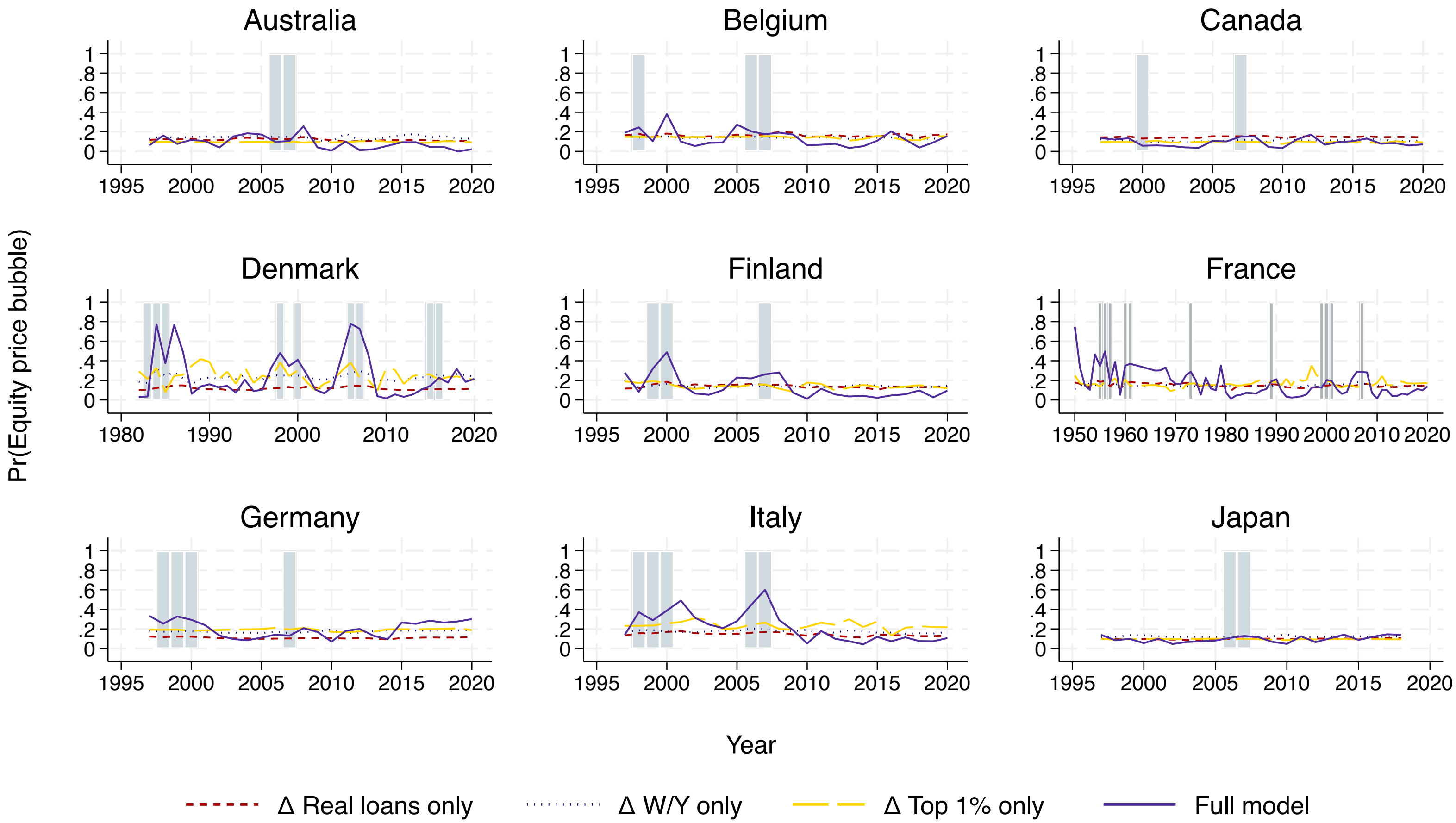
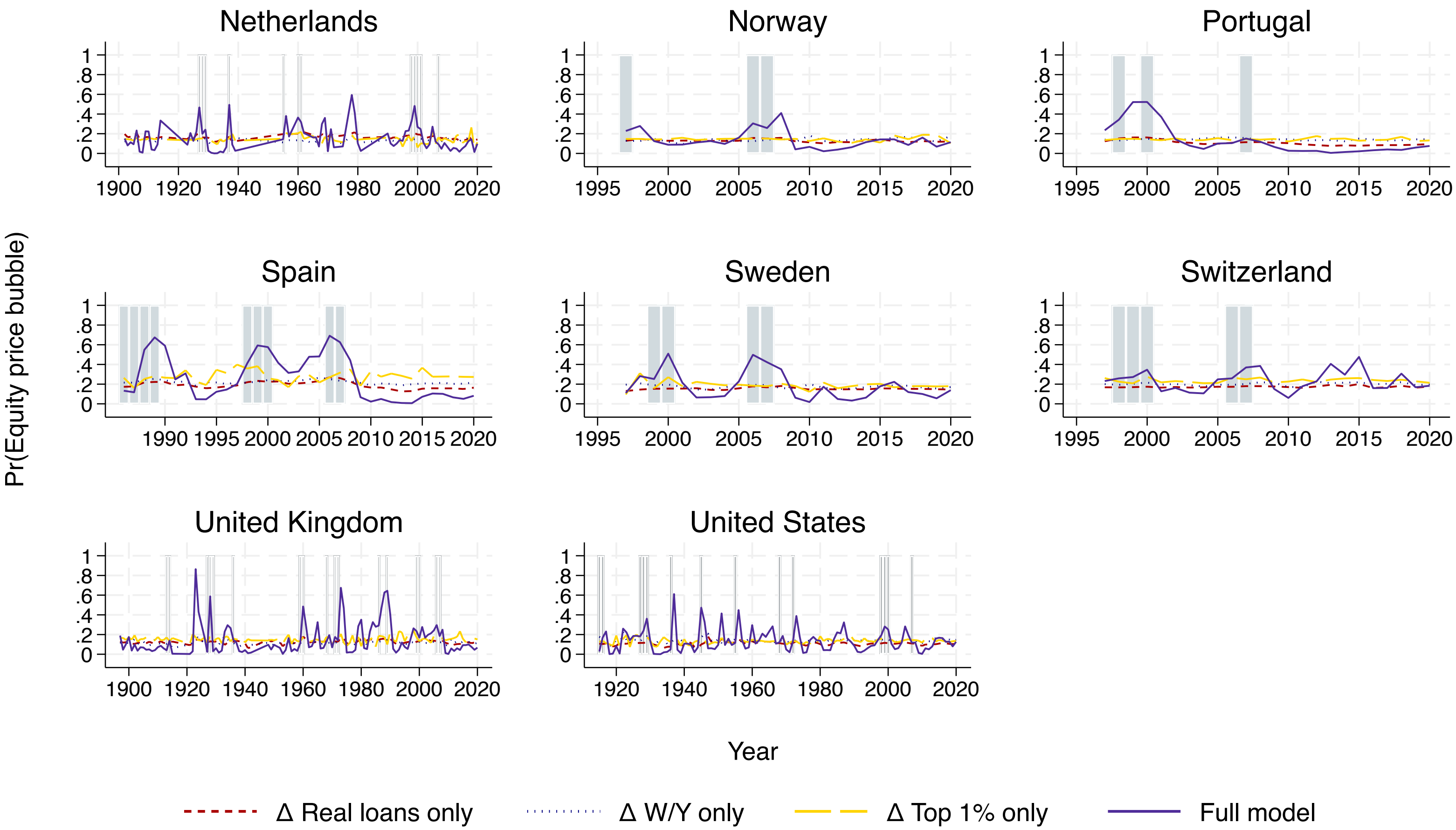


Figure 14: Predictions of equity price bubbles (continued)



Notes: This figure shows the probabilities of equity price bubbles for each country in our final sample, as predicted by different models from Table 14. It compares the in-sample predictions from the model in column (2), which includes growth in real loans and country fixed effects; column (4), which adds growth in the private wealth-income ratio and country fixed effects; column (6), which includes the growth in the share of wealth held by the top 1% along with country fixed effects; and the final model in column (9), which combines all three variables with additional controls and country fixed effects. The shaded areas represent the first year of a financial crisis event, as identified in the Jordà-Schularick-Taylor a financial crisis chronology. *Source*: Own estimations using data from the Macrohistory Database and WID.

5.3.4 Robustness checks of equity price bubble results

In line with the analysis of house price bubbles, we conduct several robustness checks to validate the main findings regarding the role of private wealth accumulation and wealth inequality on the probability of equity price bubbles. Table 15 presents the results of the analysis using the growth in the loans-to-GDP ratio as an alternative measure of credit growth. In general, except for minor variations in effect sizes, these results remain consistent with the main findings.

Table 15: Wealth concentration, loans-to-GDP ratio and equity price bubbles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Logit regression coefficients								
Δ log (Loans/GDP)$_{t-1}$	1.625**	1.708**					5.695**	6.130**	8.886***
	(0.824)	(0.816)					(2.527)	(2.756)	(2.845)
Δ log (W/Y)$_{t-1}$			3.286	3.273			8.341***	8.332***	12.698**
			(2.291)	(2.294)			(2.348)	(2.426)	(5.629)
Δ log Top 1%$_{t-1}$					6.492***	5.737***	5.269***	4.684***	3.569***
					(1.532)	(1.676)	(1.338)	(1.448)	(1.309)
	Panel B: Average marginal effects								
Δ log (Loans/GDP)$_{t-1}$	0.197*	0.206**					0.727**	0.770**	1.036***
	(0.101)	(0.097)					(0.329)	(0.339)	(0.316)
Δ log (W/Y)$_{t-1}$			0.422	0.418			1.065***	1.047***	1.480**
			(0.290)	(0.289)			(0.306)	(0.300)	(0.604)
Δ log Top 1%$_{t-1}$					0.876***	0.763***	0.673***	0.588***	0.416***
					(0.191)	(0.219)	(0.154)	(0.182)	(0.146)
N	2,056	2,056	1,291	1,291	706	706	684	684	654
Countries	17	17	17	17	17	17	17	17	17
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Controls	No	No	No	No	No	No	No	No	Yes
Pseudo R^2	0.004	0.009	0.007	0.014	0.012	0.025	0.058	0.073	0.159
Pseudolikelihood	-835.127	-830.358	-547.868	-543.674	-310.113	-305.821	-284.273	-279.768	-246.458
AUC	0.570	0.576	0.599	0.592	0.607	0.627	0.683	0.697	0.782
Standard error	0.018	0.018	0.022	0.022	0.029	0.028	0.027	0.027	0.024

Notes: This table presents the results from logit models for equity price bubbles, highlighting wealth inequality as the main variable of interest along with other key factors. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. The dependent variable is set to 1 when, in any given country, the log of the real equity price rises by more than one standard deviation from its Hodrick–Prescott filtered trend, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 14 are included. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

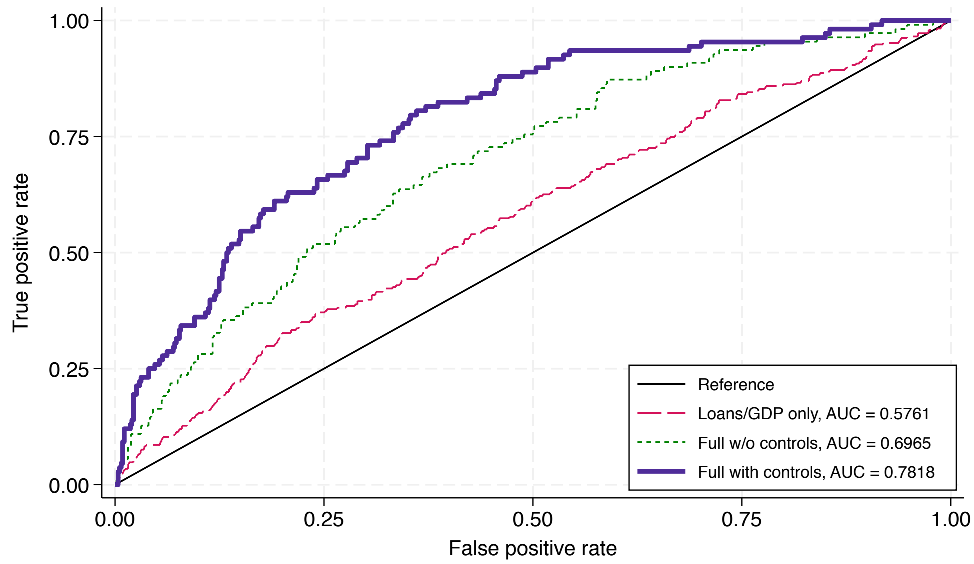
In the final model presented in column (9), the average growth of the loans-to-GDP ratio has a standard deviation of approximately 0.058. Controlling for other covariates, a one standard deviation increase in the growth of the loans-to-GDP ratio is associated with a 6 pp rise in the probability of an equity price bubble, which is statistically significant at the 1% level. For comparison, in the main analysis where we use real loans as a credit measure, the corresponding change is 6.9 pp.

We confirm that private wealth accumulation and wealth inequality are significant predictors of equity price bubbles. In this sample, the average growth in W/Y has a standard deviation of approximately 0.048. All else equal, a one standard deviation rise in the growth of W/Y is associated with a 7.7 pp increase in the probability of an equity price bubble, which is 0.1 pp lower than in the main analysis. This relationship is statistically significant at the 5% level. The average growth in the wealth share of the top 1% in this sample has a standard deviation of about 0.044. Consequently, a one standard deviation increase in the growth of the top 1% wealth corresponds to a 1.8 pp rise in the probability of an equity price bubble, which matches the findings in the main analysis. This relationship is statistically significant at the 1% level.

Furthermore, Figure 15 presents the AUC statistics for a range of models. The final model, which yields an AUC of 0.7818, outperforms the baseline model based solely on the growth of the loans-to-GDP ratio. It performs similarly to the final model where credit is measured by real loans, which results in an AUC of 0.7885. Overall, regardless of the credit definition used, private wealth accumulation and wealth inequality remain robust and statistically significant predictors of equity price bubbles.

Similarly to the analysis of house price bubbles, we define equity price bubbles based on the criteria outlined by Jordà et al. (2015b). Specifically, an equity price bubble is identified when prices rise by more than one standard deviation above their Hodrick–Prescott filtered trend and then decline by at least 15% at any point during the following three-year period. Table 16 presents these results, while Table A.13 confirms their robustness using loans-to-GDP growth as a measure of credit expansion.

Figure 15: Classification of equity price bubbles from Table 15



Notes: This figure shows the area under the receiver operating characteristic curve (AUC) for the models presented in Table 15. AUC values are reported for three models: column (2), which includes growth in the loans-to-GDP ratio and country fixed effects; column (8), which adds the growth in the private wealth-income ratio and top 1% wealth share; and column (9), which includes additional controls. *Source*: Own estimations using data from the Macrohistory Database and WID.

The links between credit growth and private wealth accumulation with equity price bubbles remain robust. All else equal, a one standard deviation rise in real loan growth is associated with a 5.8 pp increase in the probability of an equity price bubble, statistically significant at the 1% level. The corresponding result for the growth of W/Y is 7.4 pp, significant at the 5% level.

The key difference between these results and the main analysis is that the relationship between the top 1% wealth share and the alternative definition of equity price bubbles becomes insignificant. While the number of countries in the sample remains unchanged, this shift can be attributed to the reduced number of bubbles analyzed. Specifically, adopting the definition from Jordà et al. (2015b) decreases the total number of bubbles in the final sample from 108, as reported in the main analysis, to 86. Since there is no universally accepted method for empirically identifying such bubbles, these variations highlight the sensitivity of the results to different bubble definitions.

Table 16: Wealth concentration and an alternative definition of equity price bubbles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Logit regression coefficients								
Δ log real Loans$_{t-1}$	2.697***	2.820***					9.687***	10.955***	9.746***
	(0.888)	(0.852)					(2.233)	(2.851)	(2.873)
Δ log (W/Y)$_{t-1}$			3.315	3.353			10.995***	11.096***	15.662**
			(2.375)	(2.401)			(3.028)	(3.438)	(7.283)
Δ log Top 1%$_{t-1}$					5.401***	5.147***	3.689*	3.421*	2.435
					(2.024)	(1.997)	(1.963)	(1.919)	(1.959)
	Panel B: Marginal effects								
Δ log real Loans$_{t-1}$	0.280***	0.292***					0.990***	1.106***	0.956***
	(0.094)	(0.086)					(0.213)	(0.252)	(0.248)
Δ log (W/Y)$_{t-1}$			0.364	0.366			1.124***	1.120***	1.536**
			(0.254)	(0.259)			(0.275)	(0.316)	(0.624)
Δ log Top 1%$_{t-1}$					0.614***	0.582***	0.377*	0.345*	0.239
					(0.230)	(0.223)	(0.197)	(0.191)	(0.191)
N	2,078	2,078	1,291	1,291	706	706	692	692	654
Countries	17	17	17	17	17	17	17	17	17
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Controls	No	No	No	No	No	No	No	No	Yes
Pseudo R^2	0.012	0.019	0.007	0.013	0.008	0.015	0.100	0.113	0.161
Pseudolikelihood	-750.674	-745.462	-486.299	-483.290	-272.948	-271.045	-238.896	-235.495	-213.695
AUC	0.619	0.615	0.602	0.596	0.596	0.606	0.743	0.757	0.785
Standard error	0.019	0.019	0.024	0.024	0.031	0.031	0.027	0.026	0.025

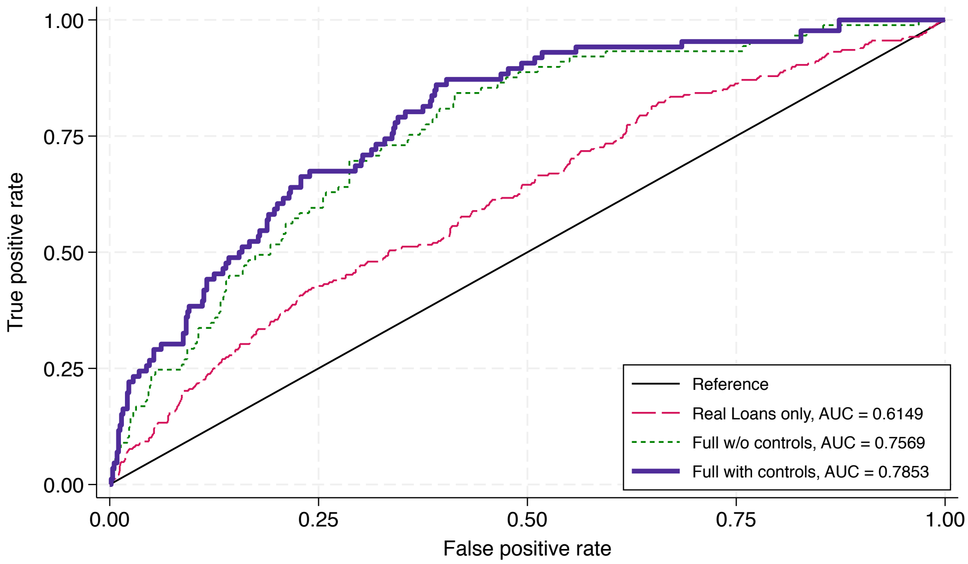
Notes: This table presents the results from logit models for equity price bubbles, highlighting wealth inequality as the main variable of interest along with other key factors. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. Following Jordà et al. (2015b), the dependent variable is set to 1 when, in any given country, (1) the log of the real equity price rises by more than one standard deviation from its Hodrick–Prescott filtered trend and (2) the price declines by at least 15% within a three-year window following the price increase, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 14 are included. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Figure 16 illustrates the AUC for various empirical models, serving as a goodness-of-fit statistic for our analyses.[22] In the baseline model, which includes only the growth in real loans, the AUC is 0.6146. However, when we incorporate the growth in W/Y and the share of wealth held by the top 1%, the AUC increases to 0.7605. Our final model, which includes all controls, achieves an AUC of 0.7885, indicating a marginally higher predictive power compared to the model without these controls. In particular, all statistics are very similar to those in the main analysis, suggesting that even with a modified definition of equity price

[22]Figure A.3 shows the AUC statistics for the corresponding models in Table A.13

bubbles, the models maintain comparable predictive power.

Figure 16: Classification of equity price bubbles from Table 16



Notes: This figure shows the area under the receiver operating characteristic curve (AUC) for the models presented in Table 16. AUC values are reported for three models: column (2), which includes growth in real loans and country fixed effects; column (8), which adds the growth in the private wealth-income ratio and top 1% wealth share; and column (9), which includes additional controls. *Source*: Own estimations using data from the Macrohistory Database and WID.

Finally, we restrict the sample to different time periods. Table A.14 presents the results where WWI and WWII are excluded.[23] Columns (1) to (5) show the results based on the main definition of equity price bubbles, while columns (6) to (10) present the results using the alternative definition adopted from Jordà et al. (2015b). The results remain consistent with the main findings. Regardless of how equity price bubbles are defined, the final models reveal a positive and highly significant relationship between private wealth accumulation and the likelihood of equity price bubbles. Although the relationship between wealth inequality and equity price bubbles is also positive in both definitions, it reaches statistical significance only with the main definition of bubbles.

In addition, Table 17 presents the results where the sample is restricted to the post-

[23]As an additional robustness check, we perform the same analysis using the growth in the loans-to-GDP ratio as an alternative measure of credit expansion. As shown in Table A.15, the results are consistent.

WWII period.[24] As shown in columns (5) and (10), the relationship between credit growth and equity price bubbles is consistent in both specifications. All else equal, a one standard deviation increase in credit growth is associated with a 6.1 pp rise in the probability of equity price bubbles in column (5) and a 5.2 pp increase in column (10), with both estimates statistically significant at the 1% level.

Table 17: Wealth concentration and equity price bubbles in the post-WWII period

	Equity bubble: Main definition					Equity bubble: Alternative definition				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Logit regression coefficients									
Δ log real Loans$_{t-1}$	5.822***			14.876***	9.568***	5.563***			14.362***	9.936***
	(2.009)			(2.717)	(2.934)	(2.012)			(3.403)	(3.768)
Δ log (W/Y)$_{t-1}$		3.728		9.165***	16.380***		3.902		12.995***	20.579***
		(3.222)		(3.002)	(4.483)		(3.357)		(3.619)	(5.243)
Δ log Top 1%$_{t-1}$			5.196***	5.327**	3.827**			4.838**	4.857*	3.388
			(1.599)	(2.243)	(1.625)			(2.135)	(2.868)	(2.560)
	Panel B: Marginal effects									
Δ log real Loans$_{t-1}$	0.711***			1.735***	1.061***	0.565***			1.377***	0.907***
	(0.232)			(0.268)	(0.310)	(0.194)			(0.276)	(0.321)
Δ log (W/Y)$_{t-1}$		0.497		1.069***	1.817***		0.428		1.246***	1.880***
		(0.423)		(0.340)	(0.469)		(0.362)		(0.319)	(0.411)
Δ log Top 1%$_{t-1}$			0.690***	0.621**	0.425**			0.524**	0.466*	0.309
			(0.209)	(0.256)	(0.180)			(0.229)	(0.273)	(0.233)
N	1,209	907	556	554	552	1,209	907	556	554	552
Countries	17	17	17	17	17	17	17	17	17	17
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	Yes	No	No	No	No	Yes
Pseudo R^2	0.038	0.019	0.032	0.148	0.198	0.037	0.020	0.021	0.145	0.200
Pseudolikelihood	-489.332	-394.068	-239.876	-210.796	-198.196	-425.007	-339.974	-206.118	-179.644	-167.964
AUC	0.669	0.612	0.635	0.776	0.806	0.667	0.620	0.616	0.781	0.810
Standard error	0.021	0.025	0.031	0.025	0.023	0.023	0.027	0.037	0.027	0.024

Notes: This table presents the results from logit models for equity price bubbles in the post-1945 period. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. In columns (1) to (5), The dependent variable is set to 1 when, in any given country, the log of the real equity price rises by more than one standard deviation from its Hodrick–Prescott filtered trend, and 0 otherwise. In columns (6) to (10), following Jordà et al. (2015b), the dependent variable is set to 1 when, in any given country, (1) the log of the real equity price rises by more than one standard deviation from its Hodrick–Prescott filtered trend and (2) the price declines by at least 15% within a three-year window following the price increase, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 14 are included. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

We confirm that the relationship between private wealth accumulation and equity price bubbles persists when the sample is restricted to the post-WWII period. Holding all other

[24] Except for small changes in the magnitude, as shown in Table A.16, findings are consistent when we change the definition of credit growth.

covariates constant, a one standard deviation increase in the growth of W/Y is associated with a 7.2 pp increase in the probability of equity price bubbles in column (5), statistically significant at the 5% level. In column (10), the corresponding effect size is 7.5 pp, significant at the 1% level.

The key difference from the main findings arises in the case of wealth inequality. The growth in the top 1% wealth share is associated with a 1.9 percentage point increase in the likelihood of equity price bubbles in column (5), significant at the 5% level, but this relationship becomes statistically insignificant in column (10). A potential explanation for this discrepancy is that the alternative definition of bubbles is more conservative, capturing fewer bubble episodes. Again, since there is no standard method for empirically identifying bubbles, these variations emphasize how sensitive the results are to the choice of bubble definition.

In summary, our analysis shows that, after controlling for key macroeconomic and financial factors, private wealth accumulation is a significant predictor of equity price bubbles, irrespective of the definition employed. The relationship between W/Y growth and equity price bubbles remains robust, even when using an alternative definition of credit expansion. This holds true whether we exclude the WWI and WWII periods or restrict the analysis to the post-WWII era.

Additionally, we find that the growth in wealth inequality is a significant predictor of equity price bubbles, independent of the definition of credit growth or the analyzed period, but only when bubbles are defined as years when the log real price of equity rises by more than one standard deviation from its noncyclical trend. In contrast, when adopting the definition of equity price bubbles proposed by Jordà et al. (2015b), which results in fewer episodes covered, this relationship becomes insignificant. Although the literature lacks consensus on the empirical estimation of bubbles, our findings suggest that the chosen definition is crucial in determining whether wealth concentration at the top percentile of the distribution is likely to trigger an equity price bubble.

6 Discussion

In the main analysis, our core finding indicates that, even after accounting for the most significant predictors of financial crises, rising wealth inequality is strongly associated with a higher probability of financial crises. This association remains robust for various crises chronologies, credit definitions, and empirical methodologies. Specifically, even after controlling for key crisis predictors, a one standard deviation increase in the growth of the top 1% wealth share is associated with a 3 to 8 pp increase in crisis probability, and this relationship is consistently significant at the 1% level. Furthermore, the lag structure in our models reveals distinct temporal dynamics among credit growth, private wealth accumulation, and wealth inequality. While a credit expansion can destabilize the financial system as early as the subsequent year, it takes a couple of years for a higher concentration of wealth at the top percentile to significantly increase the likelihood of a crisis. Similarly, increased private wealth accumulation takes three to four years to noticeably raise the risk of financial instability, such as a systemic bank run.

Our examination of transmission channels provides empirical support for the hypothesis proposed by Piketty and Zucman (2014). We find that both the private wealth-income ratio and the share of wealth held by the top 1% are positively associated with the occurrence of house and equity price bubbles, although important caveats apply. The relationship between private wealth-income ratio growth and equity price bubbles is consistently significant across various bubble definitions and time periods. The link to house price bubbles is also significant, except when the bubble definition from Jordà et al. (2015b) leads to a substantial reduction in the sample, limiting it to only five countries. Furthermore, the relationship between wealth inequality growth and house price bubbles shows sensitivity to data limitations, while its association with equity price bubbles varies depending on the chosen definition. These findings highlight the critical role of methodological rigor and bubble definitions in assessing the links between wealth concentration and asset price bubbles.

Although these results point in the same direction, there are pronounced differences from

Hauner (2020), who finds only the interaction between the national wealth-income ratio and the top 1% wealth share to be a significant predictor of financial crises, but neither of them individually. This leads him to the conclusion that an economy needs to be sufficiently wealthy before wealth inequality can trigger a crisis. In contrast, our findings suggest that this is not a necessary condition.

First, the differences in our results can be attributed to the data sources and definitions of wealth inequality. We rely on a single, consistent source for wealth inequality data, which is defined uniformly as net personal wealth, derived using the same methodology (i.e., Distributional National Accounts), and applies the same unit of analysis (i.e., adults over 20) across all countries. In contrast, Hauner (2020) utilizes various sources that define wealth differently, employ different methodologies, and use a mix of units (i.e., both individual and household). These discrepancies can lead to divergent estimates of wealth inequality, a limitation that Hauner (2020) acknowledges.

Second, unlike Hauner (2020), we focus specifically on the private wealth-income ratio, as opposed to the broader national wealth-income ratio, which includes public wealth. The ownership structure of wealth directs who benefits: while private wealth primarily enhances the welfare of individual owners, public wealth is generally intended to serve the collective good of the population. Beyond the distinct ownership implications, which suggest different effects on inequality, Chancel et al. (2022) demonstrate that over the past four decades, these wealth types have followed divergent trends: private wealth has expanded, whereas public wealth has contracted. Consequently, we emphasize the growth of the private wealth-income ratio, given its central role in shaping power dynamics that influence policy decisions, with profound implications for financial stability at the national level.

Third, our empirical approach diverges from that of Hauner (2020) in terms of methodological strategy. While his primary method employs a two-way fixed effects LPM, allowing for a robust inclusion of year fixed effects, we adopt a nonlinear model as our primary approach, aligning with the convention in the literature of modeling financial crises as binary events. For robustness checks, we incorporate impulse response functions via the LPM approach with two-way fixed effects. However, this supplementary analysis does not alter our main findings, affirming the consistency and robustness of our results across different empirical techniques.

Fourth, as a potential explanation for his findings, Hauner (2020) introduces what he refers to "an economic network hypothesis." In contrast, we empirically test house and equity price bubbles as potential transmission channels through which rising private wealth-income ratio and wealth inequality can precipitate financial crises. Beyond empirically supporting the hypothesis proposed by Piketty and Zucman (2014), which links the wealth-income ratio to asset price bubbles, our results align with the broader literature suggesting that rising wealth concentration contributes to the formation of such bubbles. Numerous studies, albeit with limited empirical evidence, indicate a shift in investment from the real economy to financial markets. This shift, driven by the pursuit of higher returns and profit maximization, has intensified demand for financial products such as collateralized debt obligations and asset-backed securities, resulting in asset bubbles that can trigger crises, such as the GFC of 2008 (see Froud et al., 2001; Lysandrou, 2011; Wisman and Baker, 2011; Wisman, 2013; Goda and Lysandrou, 2014; Goda et al., 2017).

7 Conclusion

This paper advances the understanding of the role of wealth inequality in triggering financial crises, bridging a notable gap in the existing literature on crisis predictability. While financial crises have often been interpreted as exogenous shocks, our analysis supports a growing body of research suggesting that crises are recurrent and structurally predictable events, underpinned by systemic imbalances. Specifically, we identify wealth inequality as a critical predictor, contributing to structural vulnerabilities within financial systems and enhancing the likelihood of crises through asset price bubbles.

Our empirical findings on the inequality-crisis nexus suggest that growth in wealth concentration, particularly at the top percentile, significantly raises the probability of financial crises, even after controlling for traditional predictors such as credit expansion and asset price growth. This relationship remains robust across different crisis lists, sample restrictions, and empirical specifications, emphasizing that wealth inequality acts as a destabilizing force within financial systems. Importantly, the lag structures show that the effects of private wealth accumulation and top-percentile wealth concentration on crisis probability unfold over a longer horizon compared to credit growth, which has a more immediate impact on financial instability.

Our investigation of transmission channels provides empirical support for the hypothesis suggested by Piketty and Zucman (2014), demonstrating that both the wealth-income ratio and the wealth concentration among the top 1% are robustly associated with the probability of asset price bubbles. However, our results highlight that the strength and persistence of these relationships are context-dependent. Specifically, the definition of bubbles and the sample size play an important role in shaping these associations.

Overall, this paper sheds light on the complex relationship between wealth inequality and financial crises, offering valuable insights for policy discussions on crisis prevention. Our findings indicate that financial instability is not only driven by cyclical fluctuations but can also be significantly shaped by structural wealth disparities. Addressing wealth concentration could therefore not only reduce inequality but also act as a proactive strategy to stabilize financial systems and prevent future crises. This calls for future research to integrate broader inequality metrics into crisis prediction models and examine policy interventions that can mitigate these systemic risks.

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A Appendix

Table A.1: Wealth concentration, loan-to-GDP ratio, and alternative chronologies of crises

	JST		RR		BVX		BVXN	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ log (Loans/GDP)$_{t-1}$	13.632***	27.665**	6.299**	12.619***	3.229	-5.012	7.503**	8.361*
	(4.640)	(13.061)	(2.634)	(3.408)	(4.057)	(6.345)	(3.637)	(5.056)
Δ log (Loans/GDP)$_{t-2}$	1.427	-2.077	3.226	1.633	1.813	2.657	6.680	7.042
	(5.144)	(8.792)	(4.445)	(5.045)	(2.950)	(4.592)	(4.429)	(4.408)
Δ log (Loans/GDP)$_{t-3}$	5.911	11.251	3.482	2.269	4.689	3.865	3.604	2.540
	(4.046)	(9.138)	(4.066)	(4.485)	(3.823)	(5.320)	(3.405)	(5.057)
Δ log (Loans/GDP)$_{t-4}$	-0.855	-14.395*	-3.955*	-6.849*	-3.066	-2.190	-4.199*	-4.635
	(5.203)	(7.420)	(2.105)	(3.848)	(3.175)	(5.162)	(2.256)	(3.438)
Δ log (Loans/GDP)$_{t-5}$	6.689	7.517*	2.920	3.519	4.833*	6.429	5.609**	4.170
	(4.068)	(4.464)	(2.811)	(2.179)	(2.634)	(4.362)	(2.681)	(2.595)
Δ log (W/Y)$_{t-1}$	-14.079**	-19.885**	2.106	2.548	-8.056*	-11.431	-2.569	-6.644
	(5.821)	(10.044)	(5.102)	(4.111)	(4.628)	(7.400)	(6.307)	(4.840)
Δ log (W/Y)$_{t-2}$	22.088***	22.057*	8.033*	5.135	7.103	3.279	6.650	4.132
	(8.095)	(13.298)	(4.845)	(6.235)	(5.492)	(7.287)	(6.209)	(6.317)
Δ log (W/Y)$_{t-3}$	12.907**	22.252**	1.185	2.880	6.263**	9.709**	0.853	0.326
	(5.525)	(9.914)	(3.520)	(7.996)	(2.770)	(3.865)	(4.452)	(6.655)
Δ log (W/Y)$_{t-4}$	10.898**	35.109***	8.994	18.296**	4.590	8.199	15.065**	23.186**
	(4.941)	(8.710)	(5.870)	(8.331)	(4.880)	(6.901)	(6.421)	(9.411)
Δ log (W/Y)$_{t-5}$	-5.090	-16.671	-0.550	-4.277	-0.171	0.591	-4.371	-6.704
	(5.171)	(11.242)	(3.423)	(5.845)	(3.589)	(3.270)	(4.552)	(6.156)
Δ log Top 1%$_{t-1}$	7.639**	3.930	6.014	0.444	6.630	6.121	3.806	0.049
	(3.630)	(6.479)	(4.371)	(7.370)	(4.510)	(4.977)	(4.532)	(5.790)
Δ log Top 1%$_{t-2}$	26.657***	40.711***	16.417*	19.054***	9.988**	10.268*	20.463**	22.071***
	(8.299)	(11.017)	(8.410)	(6.772)	(4.989)	(5.842)	(8.562)	(7.816)
Δ log Top 1%$_{t-3}$	2.152	-2.991	0.574	-2.349	3.341	1.771	4.240	2.959
	(3.887)	(6.468)	(2.682)	(6.012)	(3.450)	(4.740)	(2.856)	(5.030)
Δ log Top 1%$_{t-4}$	4.481	-0.854	3.831	0.215	7.782*	8.212*	2.827	0.816
	(7.242)	(13.231)	(6.934)	(6.508)	(4.429)	(4.488)	(6.002)	(5.546)
Δ log Top 1%$_{t-5}$	-2.751	-4.380	-1.497	-1.031	4.628	5.762	-1.970	-1.679
	(5.862)	(9.163)	(4.541)	(3.917)	(3.068)	(3.561)	(5.300)	(4.593)
Joint sign. of lags, χ^2:								
Δ log (Loans/GDP)	19.994	31.791	22.539	18.730	12.251	5.826	30.145	40.256
p-value	0.001	0.000	0.000	0.002	0.032	0.324	0.000	0.000
Δ log (W/Y)	23.542	24.471	3.857	15.732	18.394	11.411	21.188	14.040
p-value	0.000	0.000	0.570	0.008	0.002	0.044	0.001	0.015
Δ log Top 1%	26.728	34.253	17.876	112.066	23.024	19.707	27.205	101.610
p-value	0.000	0.000	0.003	0.000	0.000	0.001	0.000	0.000
N	538	477	388	361	518	485	486	453
Countries	13	12	11	10	15	14	13	12
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R^2	0.302	0.511	0.161	0.329	0.154	0.238	0.192	0.288
Pseudolikelihood	-55.000	-35.907	-68.560	-51.890	-103.874	-87.802	-77.266	-64.731
AUC	0.896	0.961	0.802	0.878	0.794	0.833	0.842	0.871
Standard error	0.031	0.017	0.051	0.041	0.039	0.039	0.038	0.043

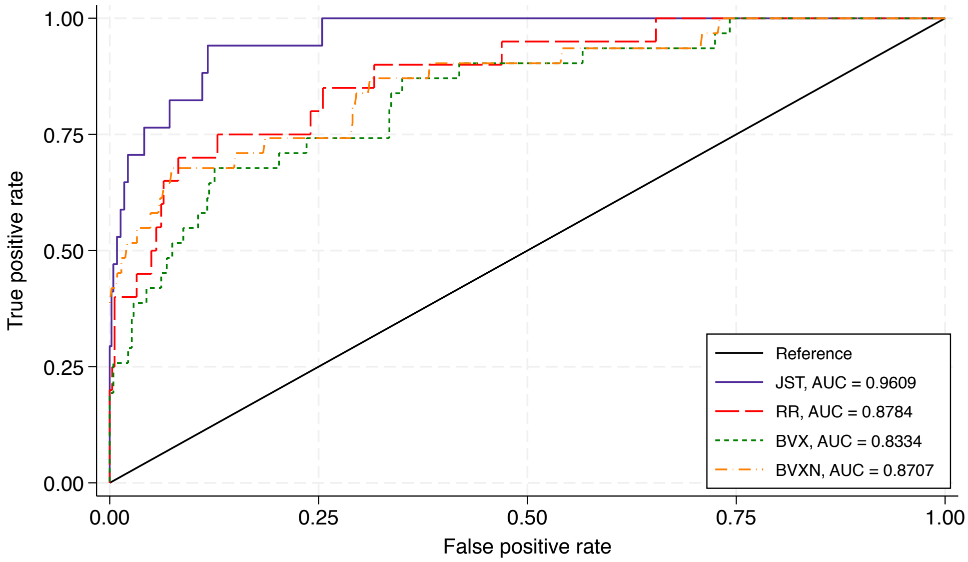
Notes: This table presents the results from logit models for systemic banking crises, emphasizing wealth inequality as the main variable of interest, along with other key factors. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). The dependent variable is set to 1 in the first year of a financial crisis event and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 2 are included. The results for goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, and the test statistics for the joint significance of the lags of the three variables shown in the table, are displayed at the bottom. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Table A.2: Average marginal effects for the final models in Table A.1

	JST			RR			BVX			BVXN		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$t-1$	0.605**	-0.435**	0.086	0.500***	0.101	0.018	-0.251	-0.573	0.307	0.325*	-0.258	0.002
	(0.250)	(0.196)	(0.137)	(0.130)	(0.167)	(0.292)	(0.324)	(0.349)	(0.249)	(0.196)	(0.184)	(0.225)
$t-2$	-0.045	0.482*	0.890***	0.065	0.204	0.755***	0.133	0.164	0.514*	0.274	0.161	0.858***
	(0.190)	(0.279)	(0.223)	(0.203)	(0.246)	(0.268)	(0.232)	(0.363)	(0.288)	(0.179)	(0.243)	(0.298)
$t-3$	0.246	0.486**	-0.065	0.090	0.114	-0.093	0.194	0.486**	0.089	0.099	0.013	0.115
	(0.182)	(0.192)	(0.139)	(0.177)	(0.312)	(0.235)	(0.264)	(0.200)	(0.236)	(0.197)	(0.258)	(0.196)
$t-4$	-0.315**	0.768***	-0.019	-0.271*	0.725**	0.009	-0.110	0.411	0.411*	-0.180	0.901***	0.032
	(0.156)	(0.175)	(0.289)	(0.144)	(0.298)	(0.258)	(0.257)	(0.327)	(0.215)	(0.133)	(0.300)	(0.215)
$t-5$	0.164	-0.364	-0.096	0.139*	-0.170	-0.041	0.322	0.030	0.289*	0.162*	-0.261	-0.065
	(0.105)	(0.233)	(0.198)	(0.081)	(0.224)	(0.158)	(0.215)	(0.165)	(0.174)	(0.097)	(0.228)	(0.183)
N	477	477	477	361	361	361	485	485	485	453	453	453
Countries	12	12	12	10	10	10	14	14	14	12	12	12
Sum of lags	0.655	0.937	0.796	0.523	0.974	0.647	0.288	0.518	1.610	0.679	0.555	0.941
Standard error	0.239	0.554	0.241	0.274	0.645	0.246	0.358	0.528	0.541	0.243	0.701	0.374
p-value	0.006	0.091	0.001	0.057	0.131	0.009	0.421	0.326	0.003	0.005	0.428	0.012

Notes: This table presents the average marginal effects (AME) from estimates in even-numbered columns of Table A.1, with five lags of each variable shown in separate columns. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). Column (1) reports the AME for the change in log real loans, column (2) for the change in log private wealth-income ratio, and column (3) for the change in the wealth share of the top 1%. The sum of the lags, along with its standard error and p-value, is also reported. Country-clustered robust standard errors are shown in parentheses. *p <0.10, **p <0.05, ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Figure A.1: Classification of financial crises from Table A.1



Notes: This figure illustrates the area under the receiver operating characteristic curve (AUC) for various models presented in Table A.1. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). It compares AUC values across four models from Table 6 : column (2), which uses the financial crises chronology from Jordà et al. (2017); column (4), which applies the systemic banking crises list from Reinhart and Rogoff (2009); column (6), which employs the new crisis list from Baron et al. (2021); and column (8), which utilizes the narrative-based crisis list from Baron et al. (2021). *Source*: Own estimations using data from the Macrohistory Database (Jordà et al., 2017; Jordà et al., 2021) and World Inequality Database (Alvaredo et al., 2020).

Table A.3: Wealth concentration and financial crises in peacetime

	JST		RR		BVX		BVXN	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ log real Loans$_{t-1}$	12.736**	34.747**	8.211	15.854***	3.441	-4.801	6.984	7.928
	(5.482)	(16.298)	(5.283)	(5.340)	(3.687)	(6.329)	(4.693)	(5.778)
Δ log real Loans$_{t-2}$	7.191	-2.742	8.843*	-0.379	0.995	-3.029	11.659**	8.690**
	(6.816)	(11.380)	(5.112)	(6.598)	(6.628)	(6.464)	(4.875)	(3.639)
Δ log real Loans$_{t-3}$	-0.207	14.413*	-1.900	1.277	0.945	5.041	-1.648	0.040
	(6.671)	(8.201)	(5.420)	(6.242)	(6.549)	(5.813)	(4.587)	(4.005)
Δ log real Loans$_{t-4}$	3.922	-17.274	-5.799	-12.313**	-2.473	-1.916	-4.876	-6.798*
	(9.793)	(12.632)	(4.766)	(5.722)	(4.398)	(6.185)	(3.565)	(4.000)
Δ log real Loans$_{t-5}$	0.395	1.935	4.921	8.453	5.553*	8.052	3.768	5.119
	(6.848)	(4.470)	(4.053)	(5.199)	(3.110)	(5.296)	(3.541)	(3.772)
Δ log (W/Y)$_{t-1}$	-10.659**	-26.093*	1.112	-4.663	-10.328**	-20.980***	-2.128	-9.259
	(5.188)	(14.951)	(6.985)	(7.995)	(5.101)	(8.049)	(5.599)	(5.872)
Δ log (W/Y)$_{t-2}$	11.878	21.856	5.615	9.825	6.815	8.204	3.593	6.676
	(11.330)	(17.000)	(8.284)	(6.543)	(6.636)	(5.200)	(6.129)	(5.658)
Δ log (W/Y)$_{t-3}$	11.870**	22.602***	3.803	3.509	8.967***	12.369***	0.604	-0.907
	(4.717)	(8.135)	(4.831)	(10.426)	(2.576)	(3.697)	(4.983)	(7.479)
Δ log (W/Y)$_{t-4}$	11.704**	41.742***	14.857***	25.935***	8.720*	10.785*	16.733***	24.042***
	(5.056)	(10.353)	(4.510)	(7.792)	(4.499)	(6.277)	(5.352)	(7.463)
Δ log (W/Y)$_{t-5}$	-4.598	-11.996	-2.050	-3.825	-0.239	0.064	-2.718	-4.228
	(4.839)	(10.132)	(3.516)	(5.583)	(3.510)	(2.831)	(3.681)	(4.219)
Δ log Top 1%$_{t-1}$	7.188**	5.498	8.015**	2.895	8.238*	7.892	4.663	1.953
	(2.998)	(7.376)	(3.628)	(7.954)	(4.930)	(5.336)	(4.007)	(6.377)
Δ log Top 1%$_{t-2}$	24.112***	45.701***	19.772*	23.265**	10.570*	10.982	20.465**	22.466***
	(8.294)	(16.560)	(10.563)	(9.531)	(5.883)	(6.869)	(9.052)	(8.323)
Δ log Top 1%$_{t-3}$	0.704	-0.615	-0.521	-1.569	3.106	2.993	2.909	3.154
	(4.989)	(7.273)	(3.997)	(6.032)	(3.408)	(4.788)	(3.514)	(5.186)
Δ log Top 1%$_{t-4}$	6.366	0.986	4.994	0.110	8.710*	8.866**	3.620	1.419
	(8.017)	(13.250)	(7.975)	(7.640)	(4.800)	(4.519)	(6.426)	(5.895)
Δ log Top 1%$_{t-5}$	-0.173	0.893	-1.513	-3.387	4.018	4.825	-0.089	-1.343
	(4.991)	(8.770)	(6.108)	(5.315)	(3.523)	(4.605)	(5.230)	(4.790)
Joint sign. of lags, χ^2:								
Δ log real Loans	1.113	5.131	2.992	18.049	0.023	4.892	5.719	35.539
p-value	0.291	0.400	0.084	0.003	0.881	0.429	0.017	0.000
Δ log (W/Y)	49.438	22.738	21.919	20.474	26.454	23.329	27.418	22.303
p-value	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.000
Δ log Top 1%	26.547	14.810	23.193	147.967	15.356	21.893	32.402	86.643
p-value	0.000	0.011	0.000	0.000	0.009	0.001	0.000	0.000
N	522	466	372	350	502	474	470	442
Countries	13	12	11	10	15	14	13	12
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R^2	0.288	0.543	0.206	0.356	0.165	0.258	0.202	0.302
Pseudolikelihood	-58.108	-33.347	-61.893	-45.682	-99.366	-80.953	-77.940	-63.077
AUC	0.897	0.965	0.835	0.904	0.812	0.862	0.842	0.875
Standard error	0.026	0.013	0.045	0.035	0.033	0.032	0.037	0.041

Notes: This table presents the results from logit models for different chronologies of systemic banking crises in peacetime. The sample excludes the periods 1914-1919, marking WWI, and 1939-1947, marking WWII and the years immediately thereafter. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). The dependent variable is set to 1 in the first year of a financial crisis event and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 2 are included. The results for goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, and the test statistics for the joint significance of the lags of the three variables shown in the table, are displayed at the bottom. Country-clustered robust standard errors are reported in parentheses. *$p<0.10$, **$p<0.05$, and ***$p<0.01$.
Source: Own estimations using data from the Macrohistory Database and WID.

Table A.4: Average marginal effects for the final models in Table A.3

	JST			RR			BVX			BVXN		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$t-1$	0.736***	-0.552**	0.116	0.583***	-0.172	0.107	-0.229	-1.002***	0.377	0.313	-0.365	0.077
	(0.268)	(0.269)	(0.156)	(0.180)	(0.288)	(0.297)	(0.304)	(0.374)	(0.256)	(0.230)	(0.232)	(0.252)
$t-2$	-0.058	0.463	0.968***	-0.014	0.362	0.856***	-0.145	0.392	0.525	0.343**	0.263	0.886***
	(0.239)	(0.346)	(0.268)	(0.242)	(0.245)	(0.330)	(0.309)	(0.248)	(0.329)	(0.153)	(0.223)	(0.324)
$t-3$	0.305**	0.479***	-0.013	0.047	0.129	-0.058	0.241	0.591***	0.143	0.002	-0.036	0.124
	(0.143)	(0.153)	(0.154)	(0.227)	(0.382)	(0.221)	(0.279)	(0.181)	(0.227)	(0.158)	(0.297)	(0.206)
$t-4$	-0.366	0.884***	0.021	-0.453**	0.954***	0.004	-0.092	0.515*	0.423**	-0.268*	0.948***	0.056
	(0.253)	(0.163)	(0.281)	(0.197)	(0.258)	(0.281)	(0.296)	(0.292)	(0.213)	(0.159)	(0.234)	(0.230)
$t-5$	0.041	-0.254	0.019	0.311*	-0.141	-0.125	0.385	0.003	0.230	0.202	-0.167	-0.053
	(0.095)	(0.201)	(0.186)	(0.188)	(0.201)	(0.201)	(0.257)	(0.135)	(0.218)	(0.155)	(0.161)	(0.192)
N	466	466	466	350	350	350	474	474	474	442	442	442
Countries	12	12	12	10	10	10	14	14	14	12	12	12
Sum of lags	0.658	1.019	1.111	0.474	1.133	0.784	0.160	0.499	1.698	0.591	0.644	1.090
Standard error	0.349	0.545	0.322	0.337	0.741	0.291	0.279	0.558	0.552	0.231	0.712	0.376
p-value	0.060	0.062	0.001	0.159	0.127	0.007	0.567	0.371	0.002	0.011	0.366	0.004

Notes: This table presents the average marginal effects (AME) from estimates in even-numbered columns of Table A.3, with the five lags of each variable arranged into separate columns. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). Column (1) reports the AME for the change in log real loans, column (2) for the change in log private wealth-income ratio, and column (3) for the change in the wealth share of the top 1%. The sum of the lags, along with its standard error and p-value, is also reported. Country-clustered robust standard errors are shown in parentheses. *p <0.10, **p <0.05, ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Table A.5: Wealth concentration, loan-to-GDP ratio, and financial crises in peacetime

	JST		RR		BVX		BVXN	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ log (Loans/GDP)$_{t-1}$	17.138***	48.701*	9.896**	15.418***	2.845	-4.434	9.295**	9.248
	(5.197)	(28.639)	(4.506)	(5.110)	(4.763)	(7.359)	(4.502)	(5.906)
Δ log (Loans/GDP)$_{t-2}$	0.280	-17.127	3.762	0.927	2.498	2.453	6.085	6.073
	(4.421)	(19.358)	(4.922)	(7.948)	(3.215)	(5.064)	(4.909)	(4.996)
Δ log (Loans/GDP)$_{t-3}$	5.796	14.603	3.267	3.358	4.778	4.963	3.106	2.849
	(3.580)	(9.861)	(3.682)	(5.857)	(4.051)	(5.597)	(3.301)	(5.176)
Δ log (Loans/GDP)$_{t-4}$	-3.989	-26.945***	-6.737**	-10.885*	-3.803	-3.743	-5.030*	-6.275
	(5.803)	(10.079)	(2.828)	(5.567)	(3.140)	(6.077)	(2.739)	(4.518)
Δ log (Loans/GDP)$_{t-5}$	7.455*	10.094***	5.056*	5.887**	6.496**	8.299*	5.269**	4.010*
	(3.867)	(3.715)	(2.909)	(2.588)	(3.021)	(4.610)	(2.617)	(2.257)
Δ log (W/Y)$_{t-1}$	-13.046**	-34.435*	2.121	-4.930	-10.416*	-20.409**	-2.071	-9.426
	(6.063)	(18.473)	(7.830)	(6.941)	(5.803)	(8.066)	(7.005)	(6.778)
Δ log (W/Y)$_{t-2}$	22.467***	33.597**	10.280*	10.405*	8.559	7.401	6.505	4.757
	(8.066)	(16.611)	(5.700)	(5.984)	(5.446)	(5.929)	(6.214)	(6.215)
Δ log (W/Y)$_{t-3}$	14.249**	22.969**	4.132	3.298	8.444**	10.318**	0.968	-0.544
	(5.917)	(10.110)	(5.849)	(8.570)	(3.365)	(4.770)	(4.926)	(6.505)
Δ log (W/Y)$_{t-4}$	10.104**	45.809***	12.471**	22.559**	7.231	9.963	14.814**	22.594**
	(4.074)	(12.179)	(5.428)	(8.769)	(5.370)	(7.682)	(5.837)	(9.112)
Δ log (W/Y)$_{t-5}$	-6.286	-16.072*	-2.641	-6.739	-1.765	-1.562	-4.667	-6.440
	(4.629)	(8.307)	(3.646)	(6.403)	(4.238)	(3.053)	(4.471)	(5.459)
Δ log Top 1%$_{t-1}$	6.969*	4.231	7.313*	2.662	8.111	8.005	3.569	0.368
	(3.665)	(9.451)	(4.241)	(7.742)	(5.145)	(5.329)	(4.458)	(6.453)
Δ log Top 1%$_{t-2}$	27.507***	52.774***	19.757**	21.855**	10.700*	10.648	20.571**	22.162***
	(8.463)	(15.783)	(9.916)	(8.713)	(5.678)	(6.522)	(8.370)	(7.941)
Δ log Top 1%$_{t-3}$	1.080	-3.751	0.586	-0.831	4.082	3.187	3.813	3.298
	(3.676)	(8.492)	(3.033)	(6.838)	(3.479)	(4.926)	(2.547)	(5.550)
Δ log Top 1%$_{t-4}$	4.558	-0.187	3.846	-0.332	8.408*	9.176**	2.795	0.889
	(7.502)	(14.072)	(7.773)	(7.766)	(4.459)	(4.673)	(5.993)	(5.747)
Δ log Top 1%$_{t-5}$	-2.590	-4.140	-3.614	-3.981	3.686	4.146	-1.946	-1.681
	(5.500)	(9.730)	(6.080)	(5.207)	(3.603)	(4.292)	(5.015)	(4.595)
Joint sign. of lags, χ^2:								
Δ log (Loans/GDP)	20.080	19.268	12.050	12.236	16.226	7.234	25.116	67.188
p-value	0.001	0.002	0.034	0.032	0.006	0.204	0.000	0.000
Δ log (W/Y)	29.901	19.040	11.406	11.434	23.018	20.661	27.918	16.309
p-value	0.000	0.002	0.044	0.043	0.000	0.001	0.000	0.006
Δ log Top 1%	27.704	13.717	22.833	106.958	18.546	19.890	28.945	96.014
p-value	0.000	0.018	0.000	0.000	0.002	0.001	0.000	0.000
N	515	462	365	346	495	470	463	438
Countries	13	12	11	10	15	14	13	12
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R^2	0.305	0.561	0.210	0.348	0.181	0.256	0.187	0.294
Pseudolikelihood	-54.260	-31.939	-58.958	-46.123	-94.941	-80.983	-76.776	-63.620
AUC	0.895	0.969	0.842	0.900	0.821	0.858	0.836	0.870
Standard error	0.031	0.014	0.047	0.037	0.036	0.035	0.040	0.045

Notes: This table presents the results from logit models for different chronologies of systemic banking crises in peacetime. The sample excludes the periods 1914-1919, marking WWI, and 1939-1947, marking WWII and the years immediately thereafter. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). The dependent variable is set to 1 in the first year of a financial crisis event and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 2 are included. The results for goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, and the test statistics for the joint significance of the lags of the three variables shown in the table, are displayed at the bottom. Country-clustered robust standard errors are reported in parentheses. *$p <0.10$, **$p <0.05$, and ***$p <0.01$. *Source*: Own estimations using data from the Macrohistory Database and WID.

Table A.6: Average marginal effects for the final models Table A.5

	JST			RR			BVX			BVXN		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$t-1$	1.018**	-0.720**	0.088	0.577***	-0.184	0.100	-0.213	-0.981***	0.385	0.368	-0.375	0.015
	(0.506)	(0.320)	(0.193)	(0.171)	(0.253)	(0.293)	(0.357)	(0.366)	(0.259)	(0.233)	(0.273)	(0.257)
$t-2$	-0.358	0.702**	1.103***	0.035	0.389*	0.817***	0.118	0.356	0.512	0.242	0.189	0.883***
	(0.387)	(0.304)	(0.233)	(0.298)	(0.229)	(0.308)	(0.245)	(0.281)	(0.317)	(0.210)	(0.245)	(0.315)
$t-3$	0.305*	0.480***	-0.078	0.126	0.123	-0.031	0.239	0.496**	0.153	0.113	-0.022	0.131
	(0.180)	(0.186)	(0.176)	(0.217)	(0.318)	(0.255)	(0.265)	(0.239)	(0.235)	(0.206)	(0.260)	(0.223)
$t-4$	-0.563***	0.957***	-0.004	-0.407**	0.844***	-0.012	-0.180	0.479	0.441**	-0.250	0.900***	0.035
	(0.169)	(0.185)	(0.294)	(0.197)	(0.294)	(0.291)	(0.290)	(0.354)	(0.220)	(0.174)	(0.291)	(0.227)
$t-5$	0.211***	-0.336**	-0.087	0.220**	-0.252	-0.149	0.399*	-0.075	0.199	0.160*	-0.256	-0.067
	(0.076)	(0.159)	(0.202)	(0.089)	(0.230)	(0.202)	(0.222)	(0.145)	(0.204)	(0.088)	(0.205)	(0.188)
N	462	462	462	346	346	346	470	470	470	438	438	438
Countries	12	12	12	10	10	10	14	14	14	12	12	12
Sum of lags	0.613	1.084	1.023	0.550	0.920	0.725	0.362	0.275	1.690	0.633	0.436	0.997
Standard error	0.343	0.573	0.454	0.313	0.722	0.249	0.352	0.596	0.558	0.261	0.819	0.382
p-value	0.074	0.059	0.024	0.079	0.202	0.004	0.303	0.645	0.002	0.015	0.595	0.009

Notes: This table presents the average marginal effects (AME) from estimates in even-numbered columns of Table A.5, with the five lags of each variable arranged into separate columns. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). Column (1) reports the AME for the change in log real loans, column (2) for the change in log private wealth-income ratio, and column (3) for the change in the wealth share of the top 1%. The sum of the lags, along with its standard error and p-value, is also reported. Country-clustered robust standard errors are shown in parentheses. *p <0.10, **p <0.05, ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Table A.7: Wealth concentration, loan-to-GDP ratio and financial crises in the post-WWII period

	JST		RR		BVX		BVXN	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ log (Loans/GDP)$_{t-1}$	15.303**	72.481*	0.952	9.065	2.190	-6.704	7.749*	12.721*
	(6.907)	(41.356)	(5.561)	(8.465)	(5.308)	(9.110)	(4.388)	(6.680)
Δ log (Loans/GDP)$_{t-2}$	-5.595	-33.522	2.377	-6.519	-0.430	-2.000	0.851	-1.044
	(6.590)	(21.789)	(5.237)	(14.196)	(4.284)	(7.692)	(4.794)	(7.081)
Δ log (Loans/GDP)$_{t-3}$	4.343	22.305	9.138	6.741	8.049	7.418	8.515	8.357
	(5.991)	(21.892)	(9.022)	(9.324)	(5.500)	(6.520)	(7.647)	(10.765)
Δ log (Loans/GDP)$_{t-4}$	4.658	-40.080*	-17.216	-22.467**	-7.225	-1.968	-8.396	-6.594
	(6.396)	(21.133)	(11.800)	(9.959)	(6.387)	(7.791)	(5.507)	(5.986)
Δ log (Loans/GDP)$_{t-5}$	6.592	27.208	11.951*	6.561	7.978**	6.663	8.320***	2.226
	(6.068)	(25.147)	(6.926)	(5.307)	(3.772)	(5.640)	(2.954)	(5.289)
Δ log (W/Y)$_{t-1}$	-18.397**	-67.422	-7.428	-17.745	-7.425	-16.438*	-7.412	-10.151
	(8.895)	(44.081)	(8.333)	(12.597)	(7.332)	(9.858)	(8.764)	(12.871)
Δ log (W/Y)$_{t-2}$	27.530**	74.548**	22.295	44.933**	11.001**	7.971	15.330*	17.812
	(12.761)	(30.701)	(15.045)	(19.653)	(5.607)	(7.973)	(8.812)	(10.960)
Δ log (W/Y)$_{t-3}$	17.751*	72.688	-2.382	-14.235	6.848	14.239*	2.943	6.027
	(10.763)	(57.650)	(14.116)	(16.729)	(6.193)	(7.791)	(9.709)	(11.176)
Δ log (W/Y)$_{t-4}$	19.473**	91.876*	28.110***	64.922***	9.101	12.460*	18.817**	31.025*
	(8.288)	(51.581)	(10.803)	(19.745)	(6.532)	(7.397)	(9.383)	(15.849)
Δ log (W/Y)$_{t-5}$	-13.597**	-42.416	-10.677	-17.314	-1.349	1.954	-6.681	-8.348
	(6.492)	(28.389)	(6.724)	(13.159)	(4.820)	(4.813)	(5.696)	(8.399)
Δ log Top 1%$_{t-1}$	7.892*	-14.190	9.892***	5.537	7.875	6.933	5.271	0.072
	(4.244)	(9.974)	(3.644)	(6.270)	(5.888)	(7.017)	(4.519)	(7.878)
Δ log Top 1%$_{t-2}$	27.574***	85.253*	18.657**	25.268**	9.294*	9.234	19.525**	21.123**
	(9.057)	(50.861)	(9.081)	(11.296)	(5.083)	(6.293)	(8.079)	(8.350)
Δ log Top 1%$_{t-3}$	4.938	7.380	4.711	2.701	3.678	2.350	4.994*	3.679
	(4.330)	(10.977)	(4.568)	(4.403)	(3.492)	(4.732)	(2.865)	(3.802)
Δ log Top 1%$_{t-4}$	2.188	-13.107	1.715	-7.603	7.130	7.864	1.521	-2.717
	(8.347)	(12.644)	(8.620)	(9.009)	(4.817)	(5.933)	(6.357)	(5.995)
Δ log Top 1%$_{t-5}$	-3.464	5.177	-7.310	-17.407**	2.836	4.604	-3.969	-3.866
	(5.411)	(13.742)	(6.306)	(7.122)	(3.902)	(4.915)	(5.081)	(6.149)
Joint sign. of lags, χ^2:								
Δ log (Loans/GDP)	11.474	7.822	7.773	39.764	9.072	5.618	28.037	8.668
p-value	0.043	0.166	0.169	0.000	0.106	0.345	0.000	0.123
Δ log (W/Y)	38.149	8.471	40.303	17.329	17.896	27.950	13.510	16.041
p-value	0.000	0.132	0.000	0.004	0.003	0.000	0.019	0.007
Δ log Top 1%	14.350	6.781	11.514	44.591	15.048	13.361	27.882	28.398
p-value	0.014	0.237	0.042	0.000	0.010	0.020	0.000	0.000
N	442	398	292	282	422	406	390	374
Countries	13	12	11	10	15	14	13	12
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R^2	0.320	0.634	0.247	0.461	0.164	0.265	0.223	0.369
Pseudolikelihood	-49.000	-24.539	-50.887	-34.596	-86.076	-71.046	-63.532	-49.197
AUC	0.897	0.981	0.846	0.939	0.805	0.865	0.853	0.913
Standard error	0.033	0.009	0.047	0.025	0.036	0.032	0.042	0.037

Notes: This table presents the results from logit models for different chronologies of systemic banking crises in the post-1945 period. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). The dependent variable is set to 1 in the first year of a financial crisis event and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 2 are included. The results for goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, and the test statistics for the joint significance of the lags of the three variables shown in the table, are displayed at the bottom. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Table A.8: Average marginal effects for the final models in Table A.7

	JST			RR			BVX			BVXN		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$t-1$	1.431**	-1.331**	-0.280	0.328	-0.642	0.200	-0.329	-0.806*	0.340	0.467*	-0.372	0.003
	(0.596)	(0.668)	(0.199)	(0.286)	(0.395)	(0.240)	(0.448)	(0.479)	(0.347)	(0.242)	(0.466)	(0.289)
$t-2$	-0.662*	1.472***	1.683**	-0.236	1.626**	0.914**	-0.098	0.391	0.453	-0.038	0.653	0.775***
	(0.358)	(0.390)	(0.752)	(0.504)	(0.673)	(0.366)	(0.377)	(0.388)	(0.308)	(0.258)	(0.397)	(0.290)
$t-3$	0.440	1.435	0.146	0.244	-0.515	0.098	0.364	0.699*	0.115	0.306	0.221	0.135
	(0.393)	(0.982)	(0.203)	(0.324)	(0.592)	(0.160)	(0.315)	(0.389)	(0.231)	(0.393)	(0.407)	(0.138)
$t-4$	-0.791**	1.814**	-0.259	-0.813**	2.350***	-0.275	-0.097	0.611*	0.386	-0.242	1.138**	-0.100
	(0.311)	(0.775)	(0.240)	(0.353)	(0.650)	(0.333)	(0.382)	(0.353)	(0.293)	(0.215)	(0.517)	(0.221)
$t-5$	0.537	-0.837*	0.102	0.237	-0.627	-0.630**	0.327	0.096	0.226	0.082	-0.306	-0.142
	(0.431)	(0.446)	(0.278)	(0.193)	(0.434)	(0.261)	(0.279)	(0.238)	(0.238)	(0.193)	(0.293)	(0.233)
N	398	398	398	282	282	282	406	406	406	374	374	374
Countries	12	12	12	10	10	10	14	14	14	12	12	12
Sum of lags	0.955	2.552	1.392	-0.240	2.192	0.307	0.167	0.990	1.520	0.575	1.334	0.671
Standard error	0.615	1.364	0.748	0.463	1.055	0.370	0.382	0.805	0.639	0.420	1.036	0.414
p-value	0.121	0.061	0.063	0.605	0.038	0.406	0.661	0.219	0.017	0.172	0.198	0.105

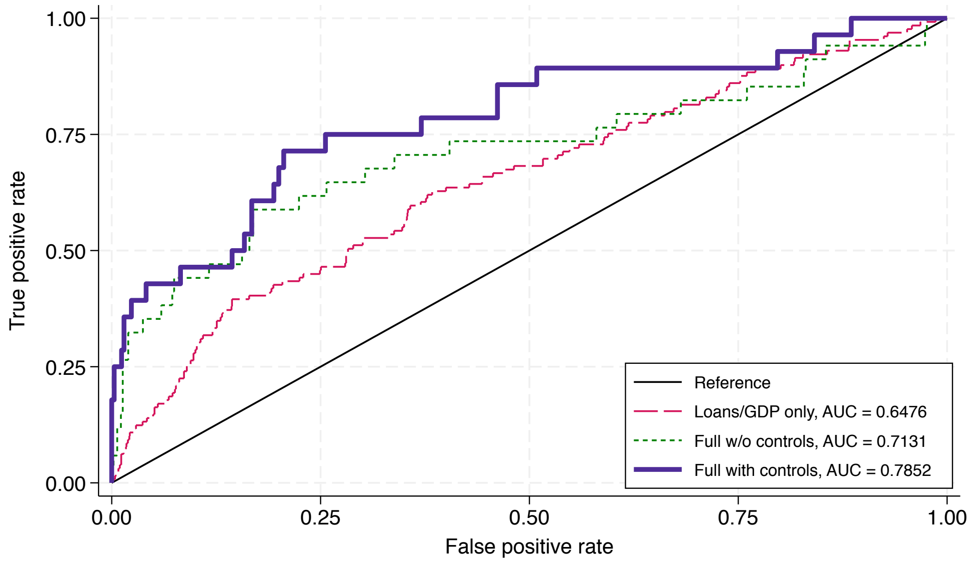
Notes: This table presents the average marginal effects (AME) from estimates in even-numbered columns of Table A.7, with the five lags of each variable arranged into separate columns. JST refers to the Jordà-Schularick-Taylor financial crisis chronology (Jordà et al., 2017), RR denotes the chronology from Reinhart and Rogoff (2009), BVX refers to the Baron-Verner-Xiong crisis list, and BVXN refers to their narrative-based crisis list (Baron et al., 2021). Column (1) reports the AME for the change in log real loans, column (2) for the change in log private wealth-income ratio, and column (3) for the change in the wealth share of the top 1%. The sum of the lags, along with its standard error and p-value, is also reported. Country-clustered robust standard errors are shown in parentheses. *p <0.10, **p <0.05, ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Table A.9: Wealth concentration, loan-to-GDP ratio and an alternative definition of house price bubbles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Logit regression coefficients								
Δ log (Loans/GDP)$_{t-1}$	4.475***	4.876***					8.154	7.585	14.229**
	(1.589)	(1.710)					(6.139)	(6.684)	(5.878)
Δ log (W/Y)$_{t-1}$			3.818**	3.561**			3.496	4.472*	6.996*
			(1.888)	(1.735)			(3.514)	(2.698)	(4.063)
Δ log Top 1%$_{t-1}$					5.889**	5.467***	4.762	4.078*	5.402**
					(2.571)	(1.800)	(3.216)	(2.117)	(2.265)
	Panel B: Marginal effects								
Δ log (Loans/GDP)$_{t-1}$	0.278***	0.305***					0.345	0.468	0.859***
	(0.101)	(0.104)					(0.292)	(0.393)	(0.289)
Δ log (W/Y)$_{t-1}$			0.201*	0.213**			0.148	0.276*	0.422*
			(0.104)	(0.102)			(0.148)	(0.163)	(0.249)
Δ log Top 1%$_{t-1}$					0.267**	0.360***	0.202	0.252**	0.326**
					(0.111)	(0.117)	(0.130)	(0.127)	(0.129)
N	1,919	1,886	1,287	1,106	775	511	751	489	368
Countries	18	17	18	13	18	7	18	7	5
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Controls	No	No	No	No	No	No	No	No	Yes
Pseudo R^2	0.016	0.035	0.008	0.029	0.007	0.035	0.042	0.083	0.190
Pseudolikelihood	-465.196	-453.972	-275.424	-258.675	-147.572	-128.087	-132.603	-113.218	-80.241
AUC	0.592	0.648	0.596	0.628	0.582	0.644	0.667	0.713	0.785
Standard error	0.028	0.027	0.037	0.035	0.051	0.043	0.058	0.057	0.052

Notes: This table presents the results from logit models for house price bubbles, highlighting wealth inequality as the main variable of interest along with other key factors. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. Following Jordà et al. (2015b), The dependent variable is set to 1 when, in any given country, (1) the log of the real house price rises by more than one standard deviation from its Hodrick–Prescott filtered trend and (2) the price declines by at least 15% within a three-year window following the price increase, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 10 are included. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. *Source*: Own estimations using data from the Macrohistory Database and WID.

Figure A.2: Classification of house price bubbles from Table A.9



Notes: This figure shows the area under the receiver operating characteristic curve (AUC) for the models presented in Table A.9. AUC values are reported for three models: column (2), which includes the growth in loan-to-GDP ratio and country fixed effects; column (8), which adds the growth in the private wealth-income ratio and top 1% wealth share; and column (9), which includes additional controls. *Source*: Own estimations using data from the Macrohistory Database and WID.

Table A.10: Wealth concentration and house price bubbles in peacetime

	House bubble: Main definition					House bubble: Alternative definition				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Logit regression coefficients									
Δ log real Loans$_{t-1}$	8.957***			10.185**	11.744***	7.633***			13.997*	11.975**
	(2.200)			(4.278)	(4.368)	(1.639)			(7.219)	(4.865)
Δ log (W/Y)$_{t-1}$		6.048**		11.486***	14.934***		3.852*		6.104	6.736
		(3.010)		(2.936)	(4.548)		(2.094)		(4.842)	(4.414)
Δ log Top 1%$_{t-1}$			-1.004	-2.092	-0.483			4.754**	3.524	5.712**
			(2.272)	(2.629)	(3.254)			(2.059)	(2.672)	(2.730)
	Panel B: Marginal effects									
Δ log real Loans$_{t-1}$	0.831***			0.913***	0.954***	0.427***			0.885**	0.713***
	(0.182)			(0.348)	(0.331)	(0.084)			(0.395)	(0.238)
Δ log (W/Y)$_{t-1}$		0.576**		1.029***	1.213***		0.206*		0.386	0.401
		(0.279)		(0.264)	(0.317)		(0.110)		(0.309)	(0.264)
Δ log Top 1%$_{t-1}$			-0.099	-0.187	-0.039			0.325**	0.223	0.340**
			(0.223)	(0.236)	(0.264)			(0.139)	(0.159)	(0.158)
N	1,772	1,124	617	611	561	1,653	1,040	383	377	350
Countries	18	15	13	13	12	16	13	6	6	5
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	Yes	No	No	No	No	Yes
Pseudo R^2	0.085	0.047	0.035	0.138	0.208	0.073	0.063	0.046	0.161	0.209
Pseudolikelihood	-569.729	-373.928	-210.477	-187.573	-156.058	-357.570	-217.562	-98.028	-85.814	-75.230
AUC	0.721	0.678	0.634	0.765	0.824	0.714	0.698	0.655	0.774	0.791
Standard error	0.019	0.026	0.033	0.032	0.029	0.027	0.033	0.048	0.054	0.048

Notes: This table presents the results from logit models for house price bubbles in peacetime. The sample excludes the periods 1914-1919, marking WWI, and 1939-1947, marking WWII and the years immediately thereafter. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. In columns (1) to (5), the dependent variable is set to 1 when, in any given country, the log of the real house price rises by more than one standard deviation from its Hodrick–Prescott filtered trend, and 0 otherwise. In columns (6) to (10), Following Jordà et al. (2015b), the dependent variable is set to 1 when, in any given country, (1) the log of the real house price rises by more than one standard deviation from its Hodrick–Prescott filtered trend and (2) the price declines by at least 15% within a three-year window following the price increase, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 10 are included. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Table A.11: Wealth concentration, loan-to-GDP ratio and house price bubbles in peacetime

	House bubble: Main definition					House bubble: Alternative definition				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Logit regression coefficients									
Δ log (Loans/GDP)$_{t-1}$	8.240***			10.033**	10.537***	7.370***			19.198***	15.621***
	(2.047)			(4.588)	(3.766)	(1.753)			(6.005)	(4.678)
Δ log (W/Y)$_{t-1}$		6.048**		10.191***	14.474***		3.852*		4.706	6.278
		(3.010)		(2.739)	(4.218)		(2.094)		(3.374)	(3.861)
Δ log Top 1%$_{t-1}$			-1.004	-1.634	-0.290			4.754**	3.961	5.823**
			(2.272)	(2.648)	(2.958)			(2.059)	(2.568)	(2.623)
	Panel B: Marginal effects									
Δ log (Loans/GDP)$_{t-1}$	0.778***			0.920**	0.863***	0.416***			1.194***	0.921***
	(0.178)			(0.389)	(0.287)	(0.093)			(0.286)	(0.197)
Δ log (W/Y)$_{t-1}$		0.576**		0.935***	1.186***		0.206*		0.293	0.370
		(0.279)		(0.251)	(0.298)		(0.110)		(0.200)	(0.226)
Δ log Top 1%$_{t-1}$			-0.099	-0.150	-0.024			0.325**	0.246	0.343**
			(0.223)	(0.243)	(0.242)			(0.139)	(0.153)	(0.148)
N	1,769	1,124	617	608	561	1,650	1,040	383	374	350
Countries	18	15	13	13	12	16	13	6	6	5
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	Yes	No	No	No	No	Yes
Pseudo R^2	0.069	0.047	0.035	0.122	0.203	0.064	0.063	0.046	0.184	0.220
Pseudolikelihood	-579.214	-373.928	-210.477	-190.609	-157.153	-360.791	-217.562	-98.028	-83.206	-74.148
AUC	0.695	0.678	0.634	0.743	0.815	0.697	0.698	0.655	0.788	0.799
Standard error	0.019	0.026	0.033	0.032	0.029	0.027	0.033	0.048	0.051	0.048

Notes: This table presents the results from logit models for house price bubbles in peacetime. The sample excludes the periods 1914-1919, marking WWI, and 1939-1947, marking WWII and the years immediately thereafter. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. In columns (1) to (5), the dependent variable is set to 1 when, in any given country, the log of the real house price rises by more than one standard deviation from its Hodrick–Prescott filtered trend, and 0 otherwise. In columns (6) to (10), Following Jordà et al. (2015b), the dependent variable is set to 1 when, in any given country, (1) the log of the real house price rises by more than one standard deviation from its Hodrick–Prescott filtered trend and (2) the price declines by at least 15% within a three-year window following the price increase, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 10 are included. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Table A.12: Wealth concentration, loan-to-GDP ratio and house price bubbles in the post-WWII period

	House bubble: Main definition					House bubble: Alternative definition				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Logit regression coefficients									
Δ log (Loans/GDP)$_{t-1}$	16.098***			18.261***	15.508**	16.052***			24.370*	46.387***
	(2.036)			(5.510)	(6.269)	(3.302)			(14.166)	(11.881)
Δ log (W/Y)$_{t-1}$		11.047*		18.352***	27.152***		5.353		8.621**	28.545***
		(6.670)		(4.740)	(5.218)		(4.290)		(3.360)	(9.015)
Δ log Top 1%$_{t-1}$			-0.337	-0.316	1.136			7.124***	8.785**	13.551**
			(1.835)	(3.097)	(2.875)			(2.421)	(3.973)	(5.756)
	Panel B: Marginal effects									
Δ log (Loans/GDP)$_{t-1}$	1.404***			1.415***	1.071***	0.843***			1.161**	1.590***
	(0.146)			(0.362)	(0.409)	(0.145)			(0.464)	(0.342)
Δ log (W/Y)$_{t-1}$		1.181*		1.422***	1.875***		0.347		0.411***	0.978***
		(0.677)		(0.365)	(0.314)		(0.270)		(0.118)	(0.329)
Δ log Top 1%$_{t-1}$			-0.032	-0.024	0.078			0.436***	0.419*	0.464**
			(0.176)	(0.240)	(0.202)			(0.145)	(0.248)	(0.206)
N	1,160	783	511	509	483	983	624	296	296	272
Countries	17	14	13	13	12	14	11	6	6	5
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	Yes	No	No	No	No	Yes
Pseudo R^2	0.137	0.057	0.023	0.230	0.317	0.127	0.044	0.051	0.307	0.497
Pseudolikelihood	-347.670	-284.024	-172.487	-135.880	-114.169	-197.183	-154.562	-69.447	-50.711	-33.358
AUC	0.766	0.704	0.609	0.811	0.876	0.759	0.670	0.686	0.886	0.952
Standard error	0.023	0.028	0.039	0.033	0.024	0.037	0.044	0.057	0.045	0.016

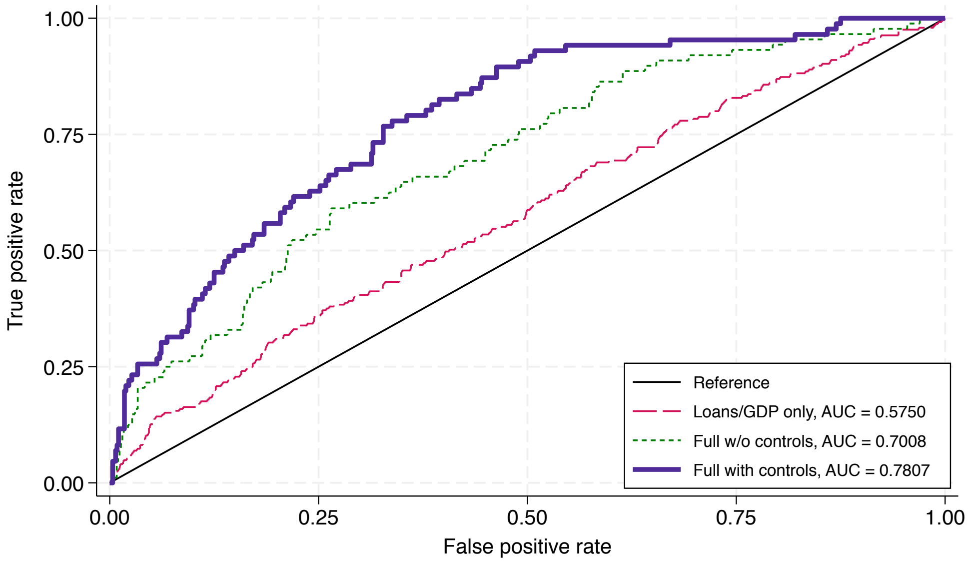
Notes: This table presents the results from logit models for house price bubbles in the post-1945 period. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. In columns (1) to (5), The dependent variable is set to 1 when, in any given country, the log of the real house price rises by more than one standard deviation from its Hodrick–Prescott filtered trend, and 0 otherwise. In columns (6) to (10), following Jordà et al. (2015b), the dependent variable is set to 1 when, in any given country, (1) the log of the real house price rises by more than one standard deviation from its Hodrick–Prescott filtered trend and (2) the price declines by at least 15% within a three-year window following the price increase, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 10 are included. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Table A.13: Wealth concentration, loan-to-GDP ratio and an alternative definition equity price bubbles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Panel A: Logit regression coefficients				
Δ log (Loans/GDP)$_{t-1}$	1.596*	1.663*					5.073*	5.528*	8.692***
	(0.877)	(0.860)					(2.798)	(3.061)	(2.994)
Δ log (W/Y)$_{t-1}$			3.315	3.353			10.388***	10.473***	15.369**
			(2.375)	(2.401)			(3.060)	(3.304)	(6.861)
Δ log Top 1%$_{t-1}$					5.401***	5.147***	3.826**	3.746**	2.542
					(2.024)	(1.997)	(1.915)	(1.827)	(2.001)
					Panel B: Average marginal effects				
Δ log (Loans/GDP)$_{t-1}$	0.167*	0.173*					0.538*	0.583*	0.858***
	(0.093)	(0.089)					(0.303)	(0.315)	(0.266)
Δ log (W/Y)$_{t-1}$			0.364	0.366			1.103***	1.104***	1.517**
			(0.254)	(0.259)			(0.300)	(0.329)	(0.593)
Δ log Top 1%$_{t-1}$					0.614***	0.582***	0.406**	0.395**	0.251
					(0.230)	(0.223)	(0.200)	(0.190)	(0.193)
N	2,056	2,056	1,291	1,291	706	706	684	684	654
Countries	17	17	17	17	17	17	17	17	17
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Controls	No	No	No	No	No	No	No	No	Yes
Pseudo R^2	0.004	0.010	0.007	0.013	0.008	0.015	0.062	0.071	0.155
Pseudolikelihood	-748.231	-743.355	-486.299	-483.290	-272.948	-271.045	-246.236	-243.985	-215.143
AUC	0.566	0.575	0.602	0.596	0.596	0.606	0.696	0.701	0.781
Standard error	0.019	0.020	0.024	0.024	0.031	0.031	0.029	0.030	0.025

Notes: This table presents the results from logit models for equity price bubbles, highlighting wealth inequality as the main variable of interest along with other key factors. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. Following Jordà et al. (2015b), The dependent variable is set to 1 when, in any given country, (1) the log of the real equity price rises by more than one standard deviation from its Hodrick–Prescott filtered trend and (2) the price declines by at least 15% within a three-year window following the price increase, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 14 are included. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Figure A.3: Classification of equity price bubbles from Table A.13



Notes: This figure shows the area under the receiver operating characteristic curve (AUC) for the models presented in Table A.13. AUC values are reported for three models: column (2), which includes the growth in loan-to-GDP ratio and country fixed effects; column (8), which adds the growth in the private wealth-income ratio and top 1% wealth share; and column (9), which includes additional controls. *Source*: Own estimations using data from the Macrohistory Database and WID.

Table A.14: Wealth concentration and equity price bubbles in peacetime

	Equity bubble: Main definition					Equity bubble: Alternative definition				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Logit regression coefficients									
Δ log real Loans$_{t-1}$	3.320***			12.924***	9.605***	3.324***			12.601***	10.597***
	(1.127)			(1.713)	(2.499)	(1.200)			(2.709)	(3.131)
Δ log (W/Y)$_{t-1}$		3.844*		9.232***	11.831**		3.891*		11.515***	15.564**
		(2.020)		(2.935)	(5.703)		(2.175)		(4.107)	(7.308)
Δ log Top 1%$_{t-1}$			5.628***	4.975***	3.944**			5.161**	4.060*	3.010
			(1.716)	(1.787)	(1.540)			(2.079)	(2.173)	(2.213)
	Panel B: Marginal effects									
Δ log real Loans$_{t-1}$	0.386***			1.513***	1.099***	0.327***			1.240***	1.014***
	(0.127)			(0.172)	(0.291)	(0.115)			(0.220)	(0.283)
Δ log (W/Y)$_{t-1}$		0.472*		1.081***	1.354**		0.402*		1.133***	1.489**
		(0.244)		(0.325)	(0.596)		(0.221)		(0.364)	(0.606)
Δ log Top 1%$_{t-1}$			0.730***	0.583***	0.451**			0.556**	0.399*	0.288
			(0.219)	(0.206)	(0.178)			(0.222)	(0.211)	(0.212)
N	1,866	1,205	664	658	632	1,866	1,205	664	658	632
Countries	17	17	17	17	17	17	17	17	17	17
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	Yes	No	No	No	No	Yes
Pseudo R^2	0.024	0.017	0.028	0.128	0.170	0.027	0.016	0.019	0.122	0.173
Pseudolikelihood	-729.890	-492.758	-281.898	-251.723	-234.487	-642.966	-431.996	-245.498	-218.829	-201.657
AUC	0.628	0.602	0.630	0.763	0.795	0.631	0.607	0.612	0.761	0.798
Standard error	0.019	0.023	0.029	0.024	0.023	0.020	0.025	0.033	0.027	0.024

Notes: This table presents the results from logit models for equity price bubbles in peacetime. The sample excludes the periods 1914-1919, marking WWI, and 1939-1947, marking WWII and the years immediately thereafter. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. In columns (1) to (5), the dependent variable is set to 1 when, in any given country, the log of the real equity price rises by more than one standard deviation from its Hodrick–Prescott filtered trend, and 0 otherwise. In columns (6) to (10), Following Jordà et al. (2015b), the dependent variable is set to 1 when, in any given country, (1) the log of the real equity price rises by more than one standard deviation from its Hodrick–Prescott filtered trend and (2) the price declines by at least 15% within a three-year window following the price increase, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 14 are included. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Table A.15: Wealth concentration, loan-to-GDP ratio and equity price bubbles in peacetime

	Equity bubble: Main definition					Equity bubble: Alternative definition				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Logit regression coefficients									
Δ log (Loans/GDP)$_{t-1}$	2.020**			7.844***	9.048***	2.133**			7.572***	9.622***
	(0.957)			(2.163)	(2.697)	(1.020)			(2.575)	(2.621)
Δ log (W/Y)$_{t-1}$		3.844*		7.997***	11.363**		3.891*		10.256***	15.140**
		(2.020)		(2.537)	(5.477)		(2.175)		(3.566)	(6.830)
Δ log Top 1%$_{t-1}$			5.628***	5.141***	4.095***			5.161**	4.363**	3.181
			(1.716)	(1.697)	(1.567)			(2.079)	(2.040)	(2.234)
	Panel B: Marginal effects									
Δ log (Loans/GDP)$_{t-1}$	0.237**			0.979***	1.040***	0.212**			0.786***	0.926***
	(0.111)			(0.262)	(0.304)	(0.100)			(0.255)	(0.224)
Δ log (W/Y)$_{t-1}$		0.472*		0.998***	1.306**		0.402*		1.064***	1.457**
		(0.244)		(0.310)	(0.576)		(0.221)		(0.348)	(0.567)
Δ log Top 1%$_{t-1}$			0.730***	0.642***	0.471***			0.556**	0.453**	0.306
			(0.219)	(0.211)	(0.179)			(0.222)	(0.210)	(0.212)
N	1,863	1,205	664	655	632	1,863	1,205	664	655	632
Countries	17	17	17	17	17	17	17	17	17	17
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	Yes	No	No	No	No	Yes
Pseudo R^2	0.014	0.017	0.028	0.076	0.167	0.017	0.016	0.019	0.074	0.169
Pseudolikelihood	-736.730	-492.758	-281.898	-266.422	-235.291	-648.934	-431.996	-245.498	-230.421	-202.746
AUC	0.592	0.602	0.630	0.701	0.790	0.599	0.607	0.612	0.703	0.792
Standard error	0.019	0.023	0.029	0.027	0.023	0.021	0.025	0.033	0.031	0.025

Notes: This table presents the results from logit models for equity price bubbles in peacetime. The sample excludes the periods 1914-1919, marking WWI, and 1939-1947, marking WWII and the years immediately thereafter. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. In columns (1) to (5), the dependent variable is set to 1 when, in any given country, the log of the real equity price rises by more than one standard deviation from its Hodrick–Prescott filtered trend, and 0 otherwise. In columns (6) to (10), Following Jordà et al. (2015b), the dependent variable is set to 1 when, in any given country, (1) the log of the real equity price rises by more than one standard deviation from its Hodrick–Prescott filtered trend and (2) the price declines by at least 15% within a three-year window following the price increase, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 14 are included. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.

Table A.16: Wealth concentration, loan-to-GDP ratio and equity price bubbles in the post-WWII period

	Equity bubble: Main definition					Equity bubble: Alternative definition				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Logit regression coefficients									
Δ log (Loans/GDP)$_{t-1}$	5.658***			9.090***	8.856***	5.188***			8.463***	8.973***
	(1.810)			(3.143)	(3.023)	(1.792)			(3.182)	(3.421)
Δ log (W/Y)$_{t-1}$		3.728		9.440***	15.950***		3.902		13.115***	20.116***
		(3.222)		(3.496)	(4.486)		(3.357)		(4.030)	(5.077)
Δ log Top 1%$_{t-1}$			5.196***	5.558***	4.094**			4.838**	5.159**	3.731
			(1.599)	(2.054)	(1.656)			(2.135)	(2.625)	(2.576)
	Panel B: Marginal effects									
Δ log (Loans/GDP)$_{t-1}$	0.702***			1.133***	0.987***	0.535***			0.857***	0.824***
	(0.217)			(0.370)	(0.319)	(0.180)			(0.302)	(0.288)
Δ log (W/Y)$_{t-1}$		0.497		1.177***	1.778***		0.428		1.328***	1.847***
		(0.423)		(0.421)	(0.475)		(0.362)		(0.377)	(0.403)
Δ log Top 1%$_{t-1}$			0.690***	0.693***	0.456**			0.524**	0.523**	0.342
			(0.209)	(0.253)	(0.182)			(0.229)	(0.266)	(0.234)
N	1,204	907	556	554	552	1,204	907	556	554	552
Countries	17	17	17	17	17	17	17	17	17	17
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	Yes	No	No	No	No	Yes
Pseudo R^2	0.027	0.019	0.032	0.093	0.195	0.025	0.020	0.021	0.094	0.196
Pseudolikelihood	-494.241	-394.068	-239.876	-224.518	-199.000	-429.828	-339.974	-206.118	-190.369	-168.839
AUC	0.630	0.612	0.635	0.716	0.803	0.627	0.620	0.616	0.721	0.806
Standard error	0.022	0.025	0.031	0.029	0.024	0.024	0.027	0.037	0.032	0.025

Notes: This table presents the results from logit models for equity price bubbles in the post-1945 period. Panel A shows the logit regression coefficients and Panel B presents the corresponding average marginal effects. In columns (1) to (5), The dependent variable is set to 1 when, in any given country, the log of the real house price rises by more than one standard deviation from its Hodrick–Prescott filtered trend, and 0 otherwise. In columns (6) to (10), following Jordà et al. (2015b), the dependent variable is set to 1 when, in any given country, (1) the log of the real equity price rises by more than one standard deviation from its Hodrick–Prescott filtered trend and (2) the price declines by at least 15% within a three-year window following the price increase, and 0 otherwise. Δ represents the annual change calculated as the first difference of the variable. W/Y denotes private wealth-to-national income ratio, while Top 1% represents the share of wealth held by the top percentile of the distribution, serving as our primary measure of wealth inequality. The same controls as described in Table 14 are included. Each variable is lagged by one year. The results for the goodness-of-fit measures, including Pseudo R^2 and AUC along with its standard error, are also presented. Country-clustered robust standard errors are reported in parentheses. *p <0.10, **p <0.05, and ***p <0.01. *Source*: Own estimations using data from the Macrohistory Database and WID.