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Historical Patterns of Inequality and Productivity around Financial Crises

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Abstract

To understand the determinants of financial crises, previous research focused on developments closely related to financial markets. In contrast, this paper considers changes originating in the real economy as drivers of financial instability. Based on long-run historical data for advanced economies, I find that rising top income inequality and low productivity growth are robust predictors of crises – even outperforming well-known early-warning indicators such as credit growth. Moreover, if crises are preceded by such developments, output declines more during the subsequent recession. In addition, I show that asset booms explain the relation between income inequality and financial crises in the data.

Keywords: Financial Crises, Productivity, Income Inequality

JEL codes: E24, E44, E51, G1, G01, G20, H12, N10, N20

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1 Introduction

The 2007-09 global financial crisis has been the defining event of economics in recent times, confronting economic research with challenging questions. Why do financial crises occur? Are they more likely to take place after particular macroeconomic developments? And, once a crisis breaks out, what determines the severity of the following recession?

To understand the sources of crises, previous research has mainly focused on developments closely related to financial markets. For example, across a range of empirical studies, one key determinant of crises that has emerged is *credit growth*. Aggregate credit booms are found to be robust predictors of crises (e.g., Schularick and Taylor, 2012) and financial recessions that are preceded by credit booms tend to be more severe (e.g., Jordà, Schularick, and Taylor, 2013). In contrast, this paper considers the above questions from a different point of view. Financial crises may not only be determined by developments that are closely related to financial markets, but also by changes that originate in the "real economy".

For example, leading up to the Great Recession, the U.S. economy experienced rapid changes in both "financial" and "real" variables. As shown in Figure 1, a credit boom occurred in the pre-Great Recession period. In addition, *top income inequality* increased rapidly between 2002 and 2007 as measured by the top 1% and the top 10% income shares. These medium-run changes are part of a longer-run rise in income inequality that started around the early 1980s and that has been widely documented recently (e.g., Piketty, Saez, and Zucman, 2016). Moreover, as pointed out by Fernald (2015) among others, economy-wide indicators of *productivity growth* began to decline several years before the start of the Great Recession and more dramatically around the outbreak of the crisis. The pre-crisis trends in productivity and income inequality may have contributed to the buildup of financial instability that led to the crisis, and they may explain the slow recovery that followed.

I am interested in whether the described U.S. patterns in fact reflect more general phenomena that tend to arise around a range of different financial crises in various countries. Because financial crises are infrequent events, a long-run historical approach is needed. To this end, I combine three data sets that have been collected and made available recently. First, the Macrohistory Database by Jordà, Schularick, and Taylor (2017) contains − among other macro-financial variables − aggregate credit measures and financial crises dates for 17 advanced economies from 1870 until 2013. Second, the Long-Term Productivity Database by Bergeaud, Cette, and Lecat (2016) comprises measures of total factor productivity (TFP) and labor productivity (LP), covering the same set of countries with time series starting between 1870 and 1890. Third, from the World Wealth & Income Database, I use the income shares of the top 1% and the top 10% of the income distribution. These time series are available for 16 out of the 17 countries and are mostly available for the second half of the sample.

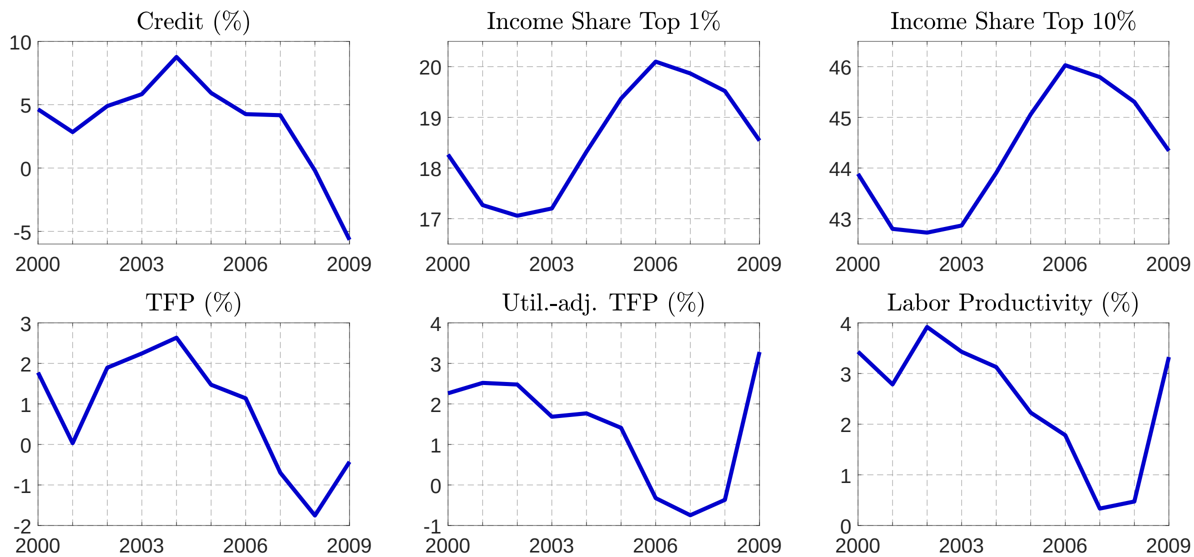


Figure 1: ***U.S. Macroeconomic Trends around the Great Recession.*** *Evolution of annual growth rate of bank credit (Source: Jordà et al., 2017), top income shares (Source: World Wealth & Income Database), and annual growth rates of various productivity measures (Source: Fernald, 2014) for the U.S. economy.*

Based on the merged data set, I obtain the following results. First, changes in the top income shares and productivity growth are strong predictors of financial crises. These results are robust to controlling for aggregate credit, a range of other macro-financial variables, and various modifications of the baseline model, and they continue to hold for alternative financial crisis dates. Changes in the top 1% income share even outperform credit in predicting crises. The same is the case for productivity growth on a post-World War II sample.

Second, I decompose changes in top income inequality that are due to labor and capital income changes of top earners. I find that capital income explains all of the relation between top income inequality and financial crises in the data. In addition, I provide evidence that realized capital gains are driving these results. Hence, rapid temporary increases in top income inequality may be a good proxy for asset booms, a point that I return to below.

Third, I find that trends in top income inequality and productivity affect not only the likelihood of crises but also the recovery period. Financial crises recessions that are preceded by unusually strong increases in top income shares or low productivity growth are characterized by stronger declines in output compared with recessions without such ex-ante trends. This pattern also holds for "normal" recessions. Further, I show that the decline in output is reflected in the response of both consumption and investment. Several channels, which I examine next, may explain these predictive relations in the data.

Income Inequality − Channels and Literature. Morelli and Atkinson (2015) and Rajan (2010), among others, have noted the potential impact of changes in income inequality on financial crises and Kirschenmann, Malinen, and Nyberg (2016) confirm this predictive relation in the data. They argue that their results imply that income inequality is a distinct driver of crises. Kumhof, Rancière, and Winant (2015) have put forth a theoretical explanation for why this may be the case. After an increase in income inequality, wealthy individuals may lend their unused income to firms or less wealthy individuals who can in turn support their own consumption, potentially to "keep up with the Joneses" (Bertrand and Morse, 2016). However, increased credit intermediation may raise the likelihood of default and the risk of a crisis.[1] Since income inequality affects the likelihood of a crisis via credit according to this view, several papers have aimed to estimate the response of credit to changes in income inequality (Bordo and Meissner, 2012; Perugini et al., 2016). However, because it is challenging to identify truly exogenous changes of income inequality in the data, the results from these studies are mixed. By contrast, I test whether changes in the top income shares contain relevant information to directly predict financial crises. This turns out to be the case. When controlling for credit, the magnitude of this relation is nearly unchanged, in particular when decomposing top income changes into labor and capital income. Hence, the results show that the inequality-credit channel is not the driving force.

In contrast to Kirschenmann et al. (2016), I further decompose changes in the top income shares into labor and capital income by top earners. I find that the results are completely driven by changes in capital income. I associate these changes to realized capital gains, one of the components of capital income as reported in tax returns (the source of the top income inequality data). Hence, the results suggest that rapid temporary increases in top income inequality are good proxies for asset booms that, in turn, precede financial crises. Interestingly, changes in the capital income of top earners continue to have predictive power even when controlling for movements in aggregate stock and house prices − likely through price changes of other assets such as nonlisted equity and corporate bonds.

Productivity − Channels and Literature. When considering the impact of productivity growth on financial instability, it is useful to distinguish between its role during *the years leading up to a crisis* and immediately *around the outbreak of a crisis*. As visible from Figure 1, productivity growth in the United States was strongly depressed around the outbreak of the 2007-09 financial crisis − either being the ultimate trigger of the crisis itself or the result of a trigger. As shown below, such a pattern typically occurs around various crises. This evidence is also confirmed by Gorton and Ordoñez (2016), who show that credit booms that end in a crisis are associated with lower productivity growth.

The fact that productivity growth is strongly depressed around the start of a crisis is also reflected in the vast majority of existing macro-finance models. Most models consider exogenous shocks to the productive capacity of firms − for example, in the form of technology or capital efficiency shocks (e.g., Brunnermeier and Sannikov, 2014; Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2014). Generally, a negative shock of this type increases financial fragility. Within a few recent models, systemic risk can also increase after an initial positive innovation or a sequence

[1] Based on Kumhof et al. (2015), Cairó and Sim (2017) study the impact of monetary policy on financial stability.

of positive shocks (e.g., Boissay, Collard, and Smets, 2016; Gorton and Ordoñez, 2016; Paul, 2017).[2] However, the typical trigger of a crisis in these models is again an adverse shock.

Besides productivity growth sharply falling around the beginning of a crisis, the results show that *persistently* low productivity growth is a good predictor of a crisis in the near future. Economies that experience prolonged periods of low productivity growth may therefore be more exposed to a financial crash. Accordingly, a buildup of risk occurs at a lower frequency than in conventional business cycle models, which generally capture high-frequency movements around a trend. The findings therefore suggest that current macro-finance models need to reexamine how to model systemic risk by allowing for lower frequency fluctuations to influence financial instability.

Other Determinants of Financial Crises. Previous research has mainly focused on changes of "financial" factors in explaining the occurrence of financial crises in the near future, such as movements in credit (e.g., Mueller, 2017), aggregate stock and house prices (e.g., Anundsen et al., 2016), and external deficits (e.g., Davis et al., 2016).[3,4] Substantial evidence suggests that bank credit expansions play a particular role with respect to financial crises. Using data on bank equity prices, Baron and Xiong (2017) argue that such credit expansions are driven by waves of optimism. Krishnamurthy and Muir (2017) show that credit spreads are unusually low in the run-up phase to a crisis and that a change in credit spreads around financial crises forecasts well the subsequent severity. Apart from credit and credit spreads, other indicators of crises have been studied recently; for example, government popularity is found to predict crises (Herrera, Ordoñez, and Trebesch, 2014). With respect to the aftermath, Romer and Romer (2017b) show that monetary and fiscal policy space prior to financial distress affects the decline in output following a crisis.

Roadmap. The next section describes the data. Section 3 is separated into two parts. First, I study the predictive power of top income inequality for financial crises, and second, that of productivity. Section 4 collects the results on the aftermath of financial crises. Section 5 concludes.

2 Data

The data used for this analysis rely on three data sets that have been collected and made available recently. These are the Macrohistory Database, the World Wealth & Income Database, and the Long-Term Productivity Database.[5]

[2] Cao and L'Huillier (2017) show that the Great Depression, the Japanese slump of the 1990s, and the Great Recession were each preceded by a technological revolution. Mendoza and Terrones (2014) find evidence that credit booms are more frequent after periods of productivity gains, particularly in industrialized countries.

[3] The focus of this paper is on the statistical predictive power of certain variables for the likelihood and severity of financial crises in the near future. This is in contrast to other parts of the literature that have either looked at the typical behavior of variables around crises or used contemporaneous movements of variables to explain financial crises (e.g., Demirgüç-Kunt and Detragiache, 1998).

[4] One exception is Kaminsky and Reinhart (1999), who considered a range of predictor variables. However, productivity growth and income inequality were not among those.

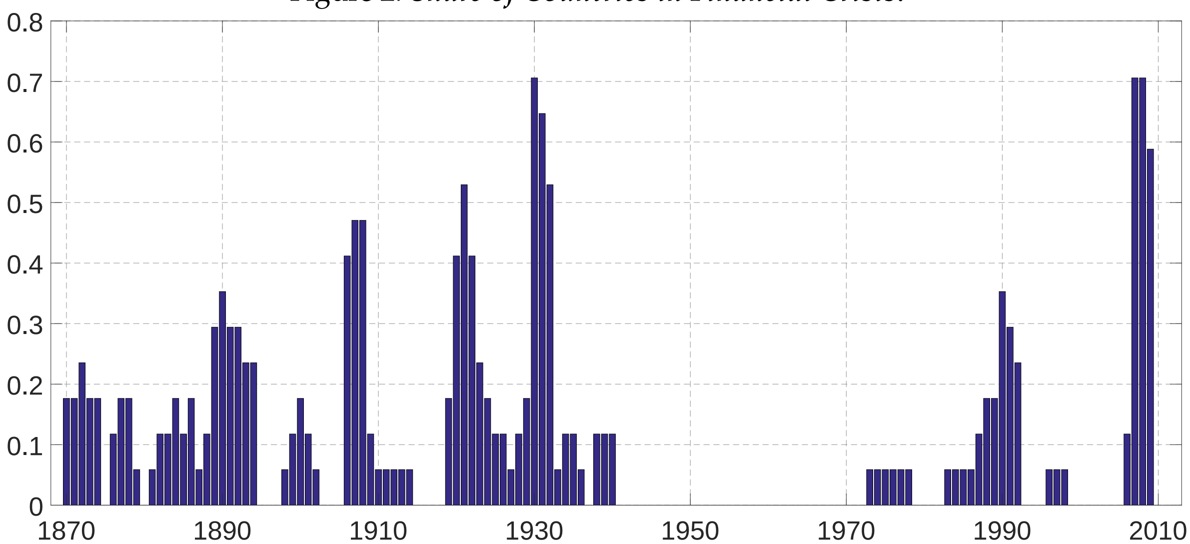
[5] All three databases are publicly available (versions used are in parentheses): Macrohistory Database (release 2), World Wealth & Income Database (January 2018), Long-Term Productivity Database (version 2.0).

2.1 Macro-Financial Data

The macro-financial data come from the Jorda-Schularick-Taylor Macrohistory Database (Jordà et al., 2017). This annual data set covers the years 1870−2013 and includes the following advanced economies: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States.[6] For these countries, the data set contains information on a number of macroeconomic and financial variables, such as GDP, consumption, investment, bank credit, mortgage lending, the current account, interest rates, and price indices (consumer, housing, stocks), among others. The house price data are based on Knoll, Schularick, and Steger (2017).

The database also incorporates indicators of financial crises events (see Table 8 in Appendix A.1.1). Using a wide variety of sources, financial crises are identified 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" (Schularick and Taylor, 2012). Figure 2 summarizes these dates graphically by showing the three-year moving sum of the share of countries within a financial crisis.[7]

Figure 2: ***Share of Countries in Financial Crisis.***



Noticeable episodes are the Great Depression around 1930 and the Great Recession around 2008 − both affected the majority of advanced economies. In contrast, coming out of World War II, most developed countries did not experience financial crises for around 30 years. To identify recessions, I follow the same methodology as Jordà et al. (2013). They use the Bry and Boschan (1971) algorithm to determine local minima and maxima in real GDP to distinguish troughs and peaks. If a financial crisis occurs within the neighborhood of a business cycle peak, then the following recession is defined as a "financial recession". The remaining recessions are termed "nonfinancial recessions". Table 9 in Appendix A.1.1 lists all business cycle peaks.

[6] For the following analysis, I exclude war periods (World War I & II).

[7] Accordingly, a country is in a financial crisis in year t if the binary crisis-indicator is equal to one in year t or $t \pm 1$.

2.2 Income Inequality Data

I use pretax income share data from the World Wealth & Income Database to measure income inequality. Income shares describe the percentage fraction of total income that accrues to a certain percentile of the income distribution. These data are constructed using a variety of sources, including income tax data, national accounts, and Pareto interpolation techniques. In what follows, I use the income shares for the top 1% and the top 10% since these have the widest coverage. Figure 3 displays the income share series for each country.

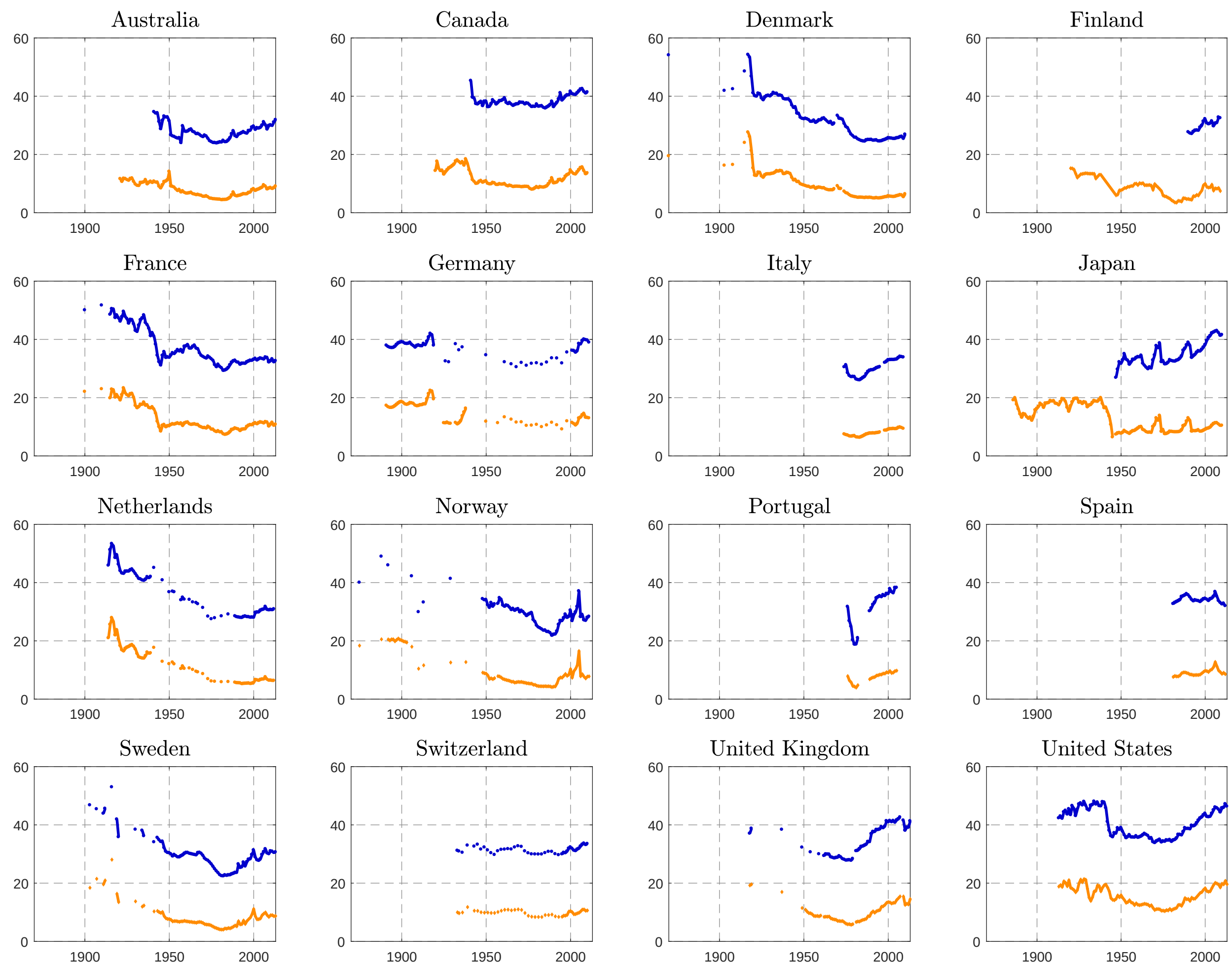


Figure 3: ***Income Shares of the Top 1% (bottom lines) and the Top 10% (upper lines).***

Noticeably, the inequality data are available for fewer years than the macro-financial data and do not include Belgium.[8] Moreover, some of the time series are interrupted. As shown below, the results are robust to interpolating data over shorter gaps. Among other interesting dynamics, the subfigure for the United States shows the recent much-discussed rise of income inequality since the beginning of the 1980s.[9]

[8]The top income share series are also largely overlapping with the data by Roine and Waldenström (2015). An exception are the years 1990−1992 for Finland, which I add. The following results remain much the same without these additional data points.

[9]In January 2006, Norway changed its shareholder income tax code. In anticipation of the reform, dividend payouts

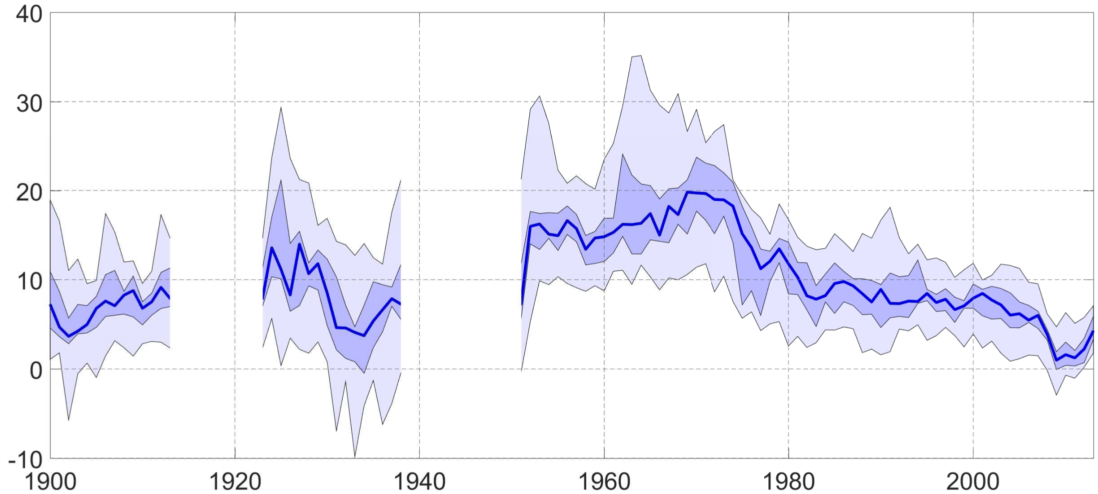
2.3 Productivity Data

Data on total factor productivity and labor productivity are obtained from the Long-Term Productivity Database by Bergeaud et al. (2016). This data set covers the same 17 advanced economies as the macro-financial database with time series starting between 1870 and 1890. TFP is calculated as the Solow residual A_t from a constant returns-to-scale Cobb-Douglas production function

$$Y_t = A_t K_t^{\alpha} H_t^{1-\alpha} \quad ,$$

where Y_t denotes real GDP, K_t the capital stock, and H_t total hours worked. K_t is the sum of equipment and buildings and is derived by applying the perpetual inventory method to investment data on each of these components.[10] Bergeaud et al. (2016) assume that the capital share α is equal to 0.3. Labor productivity is defined as the ratio of GDP to total hours worked $\frac{Y_t}{H_t}$. I additionally construct a measure of utilization-adjusted TFP following Imbs (1999) to account for the time-varying utilization of capital and labor (see Appendix A.1.2 for details). Figure 4 shows how productivity growth has evolved over time, plotting percentiles in the distribution of the four-year labor productivity growth across all countries (excluding World War I & II).[11]

Figure 4: ***Four-Year Labor Productivity Growth.*** *Median, 33^{rd}, 66^{th}, 90^{th}, and 10^{th} percentiles shown.*



Starting in the late nineteenth century, productivity growth was relatively stable, followed by the roaring twenties, and the collapse around the Great Depression. The developed world experienced unprecedented productivity growth for around 35 years after World War II − a period that is also associated with few financial crises (see Figure 2). More recently, productivity growth has slowed down significantly.

strongly increased before 2006 − resulting in a spike in the top income share series (Alstadsæter et al., 2016). The following results are robust to excluding the years around this reform for Norway.

[10] Bergeaud et al. (2016) assume that equipment depreciates at an annual rate of 10% and buildings at 2.5%. K_t is the capital stock installed at the end of period $t - 1$.

[11] The related figures for total factor productivity are shown in Appendix A.1.2.

3 Predicting Financial Crises

Figure 5 shows the typical behavior of the key variables of interest around financial crises. The patterns turn out to be quite similar to the ones for the U.S. economy before the Great Recession shown in Figure 1. The annual percentage changes of real credit and the annual changes of the top income shares increase in the years leading up to a crisis and collapse once a financial crisis breaks out. In contrast, the various measures of annual productivity growth slow down slightly during the buildup phase and strongly decline around the outbreak of a crisis.

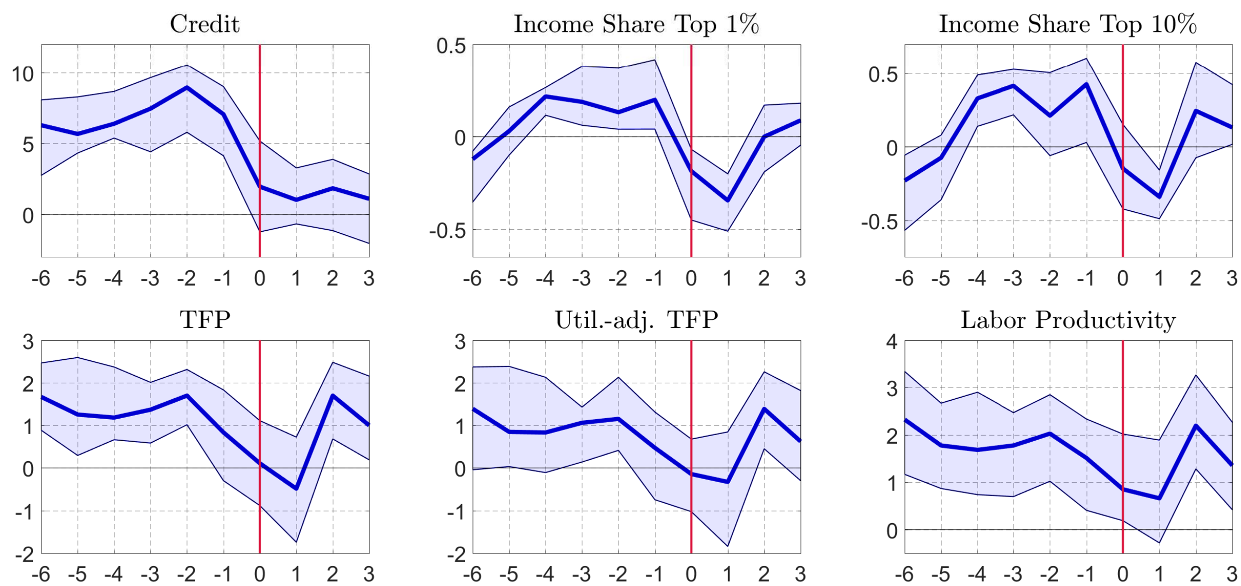


Figure 5: ***Annual (percentage) Changes around Financial Crises.*** *Median, 33rd, and 66th percentiles.*

Next, I use various statistical models to test whether top income inequality and productivity contain information to predict crises − above and beyond what is embedded in credit and other macro-financial factors. In particular, consider the probabilistic model with the log-odds ratio

$$\log\left(\frac{P[FC_{k,t}=1|\cdot]}{P[FC_{k,t}=0|\cdot]}\right) = \alpha_k + \beta_1 \Delta_h Z_{k,t-1} + \beta_2 \Delta_h X_{k,t-1} + u_{k,t} \quad , \tag{1}$$

where $FC_{k,t}$ is equal to one if a financial crisis breaks out at time t in country k and zero otherwise, following the crises dates in Jordà et al. (2017). The log-odds ratio of $FC_{k,t}$ is assumed to be a function of a country-specific constant α_k, the change of variable Z from period $t-1-h$ to $t-1$ denoted by $\Delta_h Z_{k,t-1}$, and the change of a vector of controls X from $t-1-h$ to $t-1$ defined similarly. In what follows, I normalize X and Z by their standard deviation to allow for a convenient interpretation of the marginal effects (for each respective sample). Figure 5 suggests that the medium-run movements within the five years prior to a crisis may be helpful to predict a financial crisis in the year ahead. I therefore set h equal to 4. Due to the differences in the availability of data, I first obtain evidence on the predictive power of income inequality and productivity separately.

3.1 Income Inequality

Table 1 shows the estimation results for various versions of regression (1), for which the income share of the top 1% or the top 10% take the place of variable Z. To ease comparison, I restrict the sample for all estimations to be the same even though the data availability differs across variables. The first three columns evaluate the predictive power of credit and income inequality individually, whereas the last two columns consider them jointly.

	(1)	(2)	(3)	(4)	(5)
$\Delta_4\log(\text{Credit})_{t-1}$	0.772**			0.817**	0.677**
	(0.333)			(0.339)	(0.333)
	[0.018]			[0.013]	[0.013]
Δ_4Income Share $1\%_{t-1}$		0.887***		0.954***	
		(0.258)		(0.316)	
		[0.019]		[0.015]	
Δ_4Income Share $10\%_{t-1}$			0.784***		0.738***
			(0.251)		(0.279)
			[0.018]		[0.014]
Number of crises	24	24	24	24	24
Observations	670	670	670	670	670
Countries	13	13	13	13	13
Country FE	✓	✓	✓	✓	✓
p-value	0.623	0.869	0.878	0.735	0.855
Pseudo R^2	0.086	0.109	0.090	0.159	0.130
AUROC	0.758***	0.772***	0.751***	0.825***	0.810***
	(0.053)	(0.053)	(0.052)	(0.049)	(0.047)

Table 1: ***Predicting Financial Crises.*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

The estimation results in the first column confirm a well-known finding in the literature: Aggregate measures of credit are statistically strong early-warning indicators for financial crises (Schularick and Taylor, 2012). In addition, columns 2−5 show that changes in top income shares are also statistically powerful predictors of crises (Kirschenmann et al., 2016). In fact, based on a commonly used early-warning performance measure for binary variables, the top 1% income share outperforms credit in predicting crises (see differences in AUROC between columns 1 and 2).[12,13] Columns 4 and 5 show that the predictive power of the top income shares is preserved, though

[12] AUROC stands for area under the receiver operating characteristic curve. The receiver operating characteristic curve plots true positive rates (specificity) against false positive rates (1-sensitivity) for a range of thresholds. The AUROC has the advantage that it is independent of a threshold choice. The curves that are based on the estimation results in columns 1 and 2 are plotted in Figure 12 in Appendix A.2.1.

[13] A model with country-fixed effects only has an AUROC of 0.654.

slightly smaller in magnitude, when credit is added into the regressions. The estimated coefficients also imply economically important effects. For example, a one-standard-deviation increase of the top 1% income share within a four-year window at its mean implies an increase of around 1.9 percentage points in the probability that a crisis will occur within the next year (based on the estimation results in column 2). These effects can be considered substantial, given that the average frequency of crises is around 4% in the full sample.[14]

What gives top income inequality its predictive power? To answer this question, I further decompose changes in the top income shares that are due to changes in labor income (e.g., wages and pensions) and capital income (e.g., rents, dividends, interest, and realized capital gains) of top earners. At this stage, such a detailed decomposition is only available for eight countries within the sample given data from the World Wealth & Income Database.[15] Based on this decomposition, the results are shown in Table 2 for the top 1% income share.[16,17] As visible from column 2, the predictive power is completely driven by changes in the capital income of top earners. In column 3, I additionally control for changes in credit, and stock and house prices. Even with these additional controls, changes in the capital income of top earners relative to aggregate income remain a strong predictor, both in statistical terms as well as in magnitude, which remains nearly unchanged. The inequality-credit channel can therefore not explain the results.

Due to data limitations, a further decomposition into the different types of capital income is not feasible. However, based on data from the national accounts by Piketty and Zucman (2014), I find that changes in an economy's total capital income do not predict crises (see Table 16 in Appendix A.2.1). Total capital income includes aggregate dividends, rents, and interest, but not realized capital gains.[18] Hence, the results in Table 2 are most likely explained by changes in realized capital gains as opposed to dividends, rents, and interest, which are typically more stable. Realized capital gains are indicative of a strong increase in the value of assets as captured by tax returns, the source of the underlying top income inequality data.[19,20] Interestingly, as shown in Table 2, the predictive power of changes in the capital income of top earners remains, even when controlling for aggregate stock and house prices. Hence, tax returns seem to account for asset valuation changes above and beyond aggregate stock and house price movements − for example through other assets such as nonlisted equity and corporate bonds.

[14]When excluding five years after each crisis, I find that these effects are even larger (2.2 percentage points).

[15]These countries are Australia, Canada, Spain, France, Italy, Japan, the Netherlands, and the United States.

[16]For these regressions, country-fixed effects are not included to increase the number of observations. Including country-fixed effects does not alter the results but strongly reduces the number of observations.

[17]The results for the top 10% income share are very similar and omitted for brevity.

[18]Total capital income is composed of capital income from the corporate sector, the housing sector, self-employment, net foreign capital income, and net government interest payments. The results are robust to several alternative definitions; for example, considering only distributed profits from the corporate sector.

[19]Over most of the available sample, all countries imposed a tax on capital gains. However, a caveat is that the reach of this tax differs across countries and over time.

[20]Besides an asset price increase, the results can also be explained by an increase in the number of transactions since realized capital gains are often only reported for assets that were acquired in the recent past.

	(1)	(2)	(3)
Δ_4Income Top 1%$_{t-1}$	0.928***		
	(0.341)		
	[0.016]		
Δ_4Income Top 1% Labor$_{t-1}$		-0.253	-0.180
		(0.339)	(0.456)
		[-0.004]	[-0.002]
Δ_4Income Top 1% Capital$_{t-1}$		1.084***	1.044***
		(0.286)	(0.346)
		[0.015]	[0.014]
Credit, Stock Prices, House Prices			✓
Number of crises	8	8	8
Observations	302	302	302
Countries	8	8	8
Country FE			
p-value			
Pseudo R^2	0.100	0.174	0.184
AUROC	0.747**	0.813***	0.778***
	(0.105)	(0.071)	(0.080)

Table 2: ***Predicting Financial Crises.*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Robustness. The mentioned results hold up to a range of robustness checks shown in Appendix A.2.1. For these checks, I only use the top 1% income share for brevity.[21] Starting from the regression in column 4 of Table 1, Table 10 in Appendix A.2.1 considers several deviations from this baseline. First, the results remain largely unchanged when estimating a model without country-fixed effects or an ordinary least squares regression instead of a logit regression. Second, when splitting the sample into pre- and post-WWII, the statistical relationship becomes insignificant at conventional confidence levels for the pre-WWII sample due to the few observations left, whereas the conclusions based on the post-WWII sample compared to the baseline remain much the same. Third, the potential effect of income inequality on financial crises is often mentioned with respect to the Great Depression and the Great Recession (Galbraith, 1997, Rajan, 2010, Kumhof et al., 2015). When excluding these two episodes from the sample, the relationship is still significant at the 90% confidence level, though smaller in magnitude.[22]

[21] This choice is motivated by the finding that the statistically significant relationship between financial crises and the top income shares is mainly driven by changes of the top 1% income share but not by changes in the top 2 to 10%. That is because the coefficient on the latter is not statistically different from zero at the 90% confidence level, whereas the one on the former remains significant at the 99% level when both are included in a regression together with credit.

[22] In particular, I exclude the years 2007−2013 (Great Recession) and 1929−1940 (Great Depression).

Fourth, I check whether the predictive power of income inequality is unique to financial recessions or holds more generally for nonfinancial recessions as well (using the recession definitions from Jordà et al., 2013). I find that income inequality does not help predict the start of nonfinancial recessions − nor does credit. Fifth, the results also remain much the same if one considers a change in the log of the income share instead of its absolute change. Sixth, detrending the regressors by their average over the preceding years does not change the results (using a 20-year window). Seventh, I include additional data by linearly interpolating over small gaps in the income share series. Table 15 in Appendix A.2.1 shows the estimation for which one-, two-, and three-year gaps are filled. The results are much the same.

Next, I check whether the findings depend on the specific crises dates by Jordà et al. (2017).[23] In Tables 11, 12, 13, and 14 in Appendix A.2.1, I repeat the estimation of Table 1 using various alternative crises dates. In particular, I consider the dates by Reinhart and Rogoff (2009) (available years: 1870−2010), Laeven and Valencia (2013) (1970−2011), Bordo et al. (2001) (1880−1997), and Romer and Romer (2017a) (1967-2012). The first three are annual binary indicators denoting the start of a financial crisis. In contrast, Romer and Romer (2017a) develop a semi-annual financial distress measure that ranges from 0 (no distress) to 15 (extreme distress) and can be non-zero for several years in a row. To reconcile this measure with the previous analysis, I convert it into an annual binary indicator capturing the start of a crisis.[24] Strikingly, using these various financial crises dates, the results are largely unchanged.

Further, I test whether the identified relationship might in fact be picking up the influence of another indicator. In Table 3, I control for a large set of macro-financial factors simultaneously. The initial set includes the four-year changes of short- and long-term interest rates, the consumer price index, the ratios of investment, current account, and public debt to GDP, and aggregate credit. In column 2, I also control for changes in domestic and global real GDP to proxy for worldwide trends.[25] To account for changes in asset valuations, I further include real stock and house prices in column 3 − slightly reducing the sample size. Overall, the results remain largely unchanged. Hence, even when controlling for a wide range of other macro-financial factors, changes in the top 1% income share still have predictive power for crises.[26,27]

[23]See Bordo and Meissner (2016) for a discussion on the dating of financial crises.

[24]In particular, I use two separate definitions. First, the binary indicator equals one if the financial distress measure is larger or equal to one within one year, but not in the previous year. Second, the binary indicator equals one for the start of an episode of financial distress during which the distress measure reaches 7 or more. Again, a period of distress starts at the point when the measure changes from zero to non-zero.

[25]Global GDP is defined as the sum of real GDP across all countries in the sample.

[26]In Tables 17 and 18 in Appendix A.2.1, I control for a range of variables separately. Strikingly, the magnitude and significance of the coefficient on the top 1% income share is very robust to the inclusion of these variables.

[27]Based on data from the World Wealth & Income Database, I also test for the predictive power of the national wealth-to-income ratio (see Table 19 in Appendix A.2.2). The wealth-to-income ratio is a powerful predictor of crises as well. However, when controlling for changes in real stock and house prices, key drivers of wealth (Piketty and Zucman, 2014), the coefficient becomes indistinguishable from zero. A similar test for wealth inequality is unfortunately not feasible at this stage due to data limitations (see also Saez and Zucman, 2016). For example, the World Wealth & Income Database contains wealth inequality data for only three out of the 17 countries in this paper. Even after adding

	(1)	(2)	(3)
Δ_4Income Share 1%$_{t-1}$	0.667***	0.732***	0.699***
	(0.222)	(0.223)	(0.219)
	[0.011]	[0.011]	[0.008]
Set of controls	✓	✓	✓
GDP & Global GDP		✓	✓
Stock & House Prices			✓
Number of crises	29	29	27
Observations	781	781	738
Countries	14	14	14
Country FE	✓	✓	✓
p-value	0.748	0.811	0.366
Pseudo R^2	0.163	0.176	0.227
AUROC	0.814***	0.824***	0.859***
	(0.042)	(0.039)	(0.030)

Table 3: ***Predicting Financial Crises.*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

3.2 Productivity

This section repeats the estimation of various versions of regression (1), but instead of the top income shares taking the place of variable Z, I now consider different measures of productivity. In particular, I focus on the predictive power of utilization-adjusted TFP and labor productivity as they are defined in Section 2.3 and Appendix A.1.2. Table 4 shows the estimation results.

The main findings are in columns 2−5. Both productivity measures are strong predictors of financial crises − even (more so) if credit is included. If countries experience below-average productivity growth, the likelihood of a financial crisis increases. However, the productivity measures do not outperform credit as predictors based on the considered early-warning performance measure (comparing again the differences in the AUROC measure in columns 1, 2, and 3). However, this changes when considering the post-WWII sample only, for which both productivity measures outperform credit as predictor variables (see Table 20 in Appendix A.2.3).[28,29]

observations for seven additional countries based on the data by Roine and Waldenström (2015), I do not find that wealth inequality is a statistically significant predictor of crises.

[28]The associated curves for the results in columns 1 and 3 are plotted in Figure 13 in Appendix A.2.3.

[29]A model with only country-fixed effects has an AUROC of 0.601. Compared with this model, the additional improvement from adding any of the productivity measures is therefore small (see Table 4). However, this changes for the post-WWII sample, for which the AUROC improves by around 0.075 (utilization-adjusted TFP) and 0.1 (LP), when adding changes in productivity growth to a model with only country-fixed effects (see Table 20 in Appendix A.2.3).

The estimated effects of productivity are sizable: Based on the regression results in column 5, if labor productivity growth is one standard deviation below mean, then the probability of a financial crisis occurring within the next year increases by around 1.3 percentage points.[30]

	(1)	(2)	(3)	(4)	(5)
$\Delta_4 \log(\text{Credit})_{t-1}$	0.458***			0.537***	0.597***
	(0.126)			(0.142)	(0.147)
	[0.013]			[0.014]	[0.015]
$\Delta_4 \log(\text{TFP})_{t-1}^{\text{util.-adj.}}$		-0.269**		-0.407***	
		(0.129)		(0.132)	
		[-0.008]		[-0.011]	
$\Delta_4 \log(\text{LP})_{t-1}$			-0.303***		-0.512***
			(0.115)		(0.124)
			[-0.009]		[-0.013]
Number of crises	53	53	53	53	53
Observations	1552	1552	1552	1552	1552
Countries	17	17	17	17	17
Country FE	✓	✓	✓	✓	✓
p-value	0.963	0.983	0.981	0.946	0.943
Pseudo R^2	0.044	0.024	0.025	0.058	0.066
AUROC	0.695***	0.626***	0.636***	0.711***	0.724***
	(0.035)	(0.040)	(0.038)	(0.035)	(0.032)

Table 4: ***Predicting Financial Crises.*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Robustness. As before, I take the results from Table 4 as benchmarks. I start from the ones reported in column 5, given the fact that labor productivity outperforms utilization-adjusted TFP in terms of the AUROC performance measure. From this benchmark, I consider several modifications (shown in Table 21 in Appendix A.2.3).

First, switching to a model without country-fixed effects or to ordinary least squares does not change the results. Second, the statistically significant relationship between productivity and financial crises is mainly a post-WWII phenomenon − it does not hold for a pre-WWII sample. Hence, the years immediately after post-WWII − with strong growth and few crises − seem to be important for the identified relation.

Third, the results are much the same when excluding the Great Depression and the Great Recession. Fourth, labor productivity does not have predictive power for nonfinancial recessions.

[30] When excluding five years after each crisis from the sample, I find that this effect rises to 1.8 percentage points.

Fifth, the input factor part within a Cobb-Douglas production function, given by $\frac{Y_t}{A_t} = K_t^{\alpha} H_t^{1-\alpha}$ following the notation in Section 2.3, does not have the same predictive power as productivity.

Sixth, detrending the regressors by their average over the preceding 20 years does not change the results. Last, the findings also remain much the same when using the alternative financial crises dates by Reinhart and Rogoff (2009), Laeven and Valencia (2013), Bordo et al. (2001), or Romer and Romer (2017a) (see Tables 22, 23, 24, and 25 in Appendix A.2.3). Next, I again check whether adding a range of other macroeconomic and financial variables may change the relationship between productivity and financial crises. In Table 5, I first include the same set of controls as in Table 3. Next, I add stock and house prices, and then the top 1% income share; both steps reduce the sample size.[31] Again, the predictive power of labor productivity remains intact.[32,33]

	(1)	(2)	(3)
$\Delta_4 \log(\text{LP})_{t-1}$	-0.553***	-0.550**	-0.810**
	(0.134)	(0.216)	(0.361)
	[-0.012]	[-0.010]	[-0.009]
Set of controls	✓	✓	✓
Stock & House Prices		✓	✓
Income Share 1%			✓
Number of crises	53	41	27
Observations	1387	1145	738
Countries	16	16	14
Country FE	✓	✓	✓
p-value	0.849	0.782	0.169
Pseudo R^2	0.115	0.141	0.229
AUROC	0.756***	0.778***	0.852***
	(0.033)	(0.036)	(0.035)

Table 5: ***Predicting Financial Crises.*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Last, based on a comparison of the AUROC measure, I conduct a horse race between credit, the top 1% income share, and labor productivity (see Table 28 in Appendix A.2.4).[34] Inequality wins.

[31] Due to the strong correlation between labor productivity and domestic as well as global GDP, I do not include these variables as controls.

[32] However, this is not the case for utilization-adjusted TFP.

[33] Tables 26 and 27 in Appendix A.2.3 show that both the size and the significance of the coefficients with respect to labor productivity remain largely the same, even when controlling for a range of other variables individually. There is one exception. The predictive power of labor productivity is much reduced when adding the credit-to-GDP ratio. That is because productivity and GDP are strongly positively correlated. By controlling for credit-to-GDP, one considers changes in productivity that leave this ratio unchanged in a multivariate regression and therefore positive movements between productivity and credit − pushing up the coefficient on labor productivity.

[34] For this comparison, I exclude country-fixed effects to increase the number of observations.

4 Financial and Nonfinancial Recessions

The results thus far show that both movements in top income inequality and productivity growth are informative about the likelihood of financial crises. In what follows, I study whether increases in top income inequality or low productivity growth are also able to predict the severity of recessions.

In particular, I consider the behavior of output during recessions associated with financial crises (financial recessions). In addition, I examine the path of output during "normal" recessions (nonfinancial recessions). It is well established that financial recessions are deeper and associated with slower recoveries compared with nonfinancial recessions (Jordà et al., 2013). However, the response of output also varies greatly across countries and periods during both types of recessions. Some countries experience prolonged spells of depressed output after a financial crisis, others in fact recover relatively quickly, and similar differences may arise for nonfinancial recessions. Figure 6 illustrates this variation. Based on the recession dates defined in Section 2.1, Figure 6 shows the typical percentage change of real GDP after the start of both types of recessions.

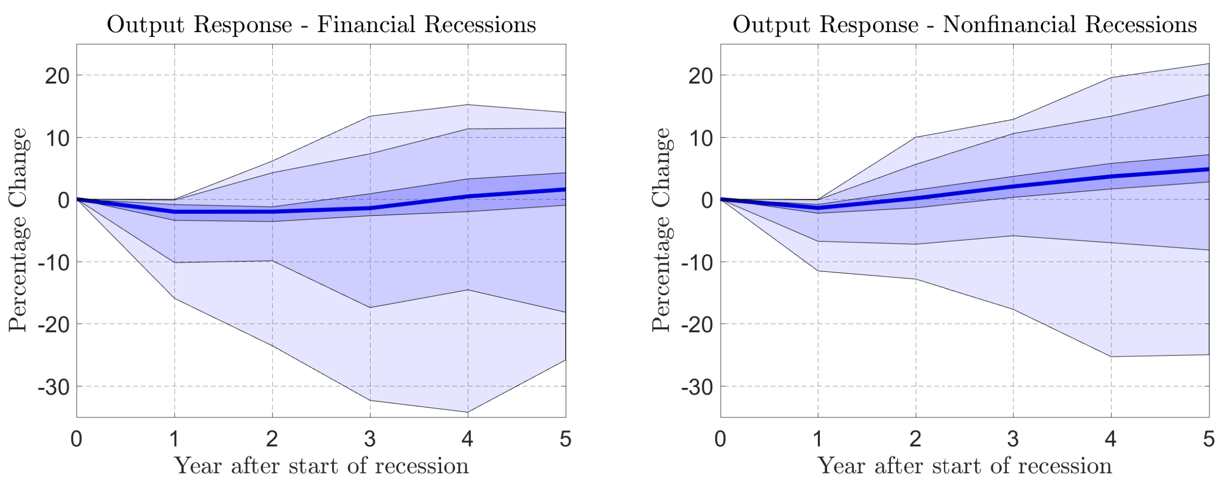


Figure 6: ***Behavior of Output during Recessions.*** *Percentage change in real GDP after the start of financial (left) and nonfinancial (right) recessions. Median, 33^{rd} and 66^{th}, 5^{th} and 95^{th}, 1^{st} and 99^{th} percentiles are shown.*

Clearly, the data show that there is substantial heterogeneity − both for financial and nonfinancial recessions. Part of this variation may be due to pre-recession trends in income inequality and productivity. To get a first sense on whether this might be the case, I distinguish between the path of output during recessions following expansions that are characterized by either increases or decreases in top income inequality and high or low productivity growth relative to their typical changes during expansions.

With respect to the start of a financial recession at time t, let $\xi^F_{k,t}$ denote the average annual change of some variable Z during the preceding expansion for country k.[35] The variable $\xi^N_{k,t}$ is defined accordingly with respect to nonfinancial recessions. For the main analysis, Z is either given by the top 1% income share or (log) labor productivity. Further, I normalize $\xi^F_{k,t}$ and $\xi^N_{k,t}$ to have mean zero and standard deviation one. Hence, one can interpret $\xi^F_{k,t}$ and $\xi^N_{k,t}$ as the *excess* change of Z over the previous boom with respect to financial and nonfinancial recessions that start at time t. Figure 7 shows the average percentage change in real GDP after the start of financial and nonfinancial recessions, depending on whether $\xi^F_{k,t}$ and $\xi^N_{k,t}$ are positive or negative.

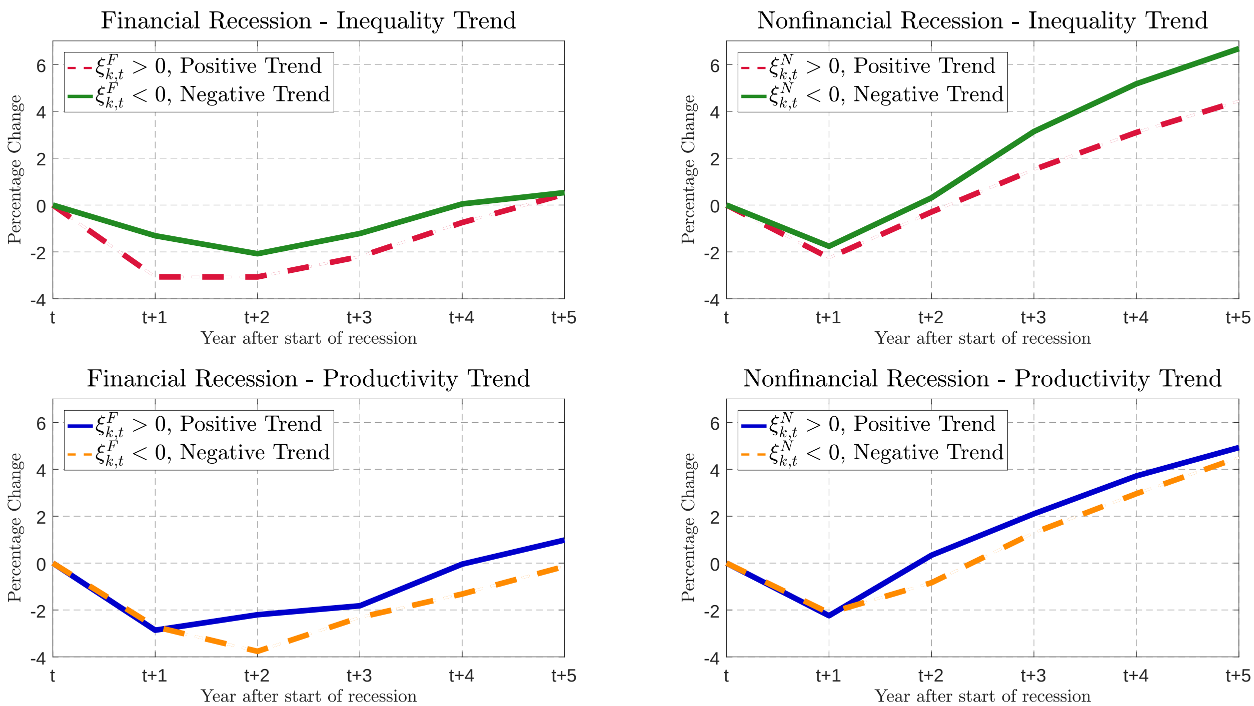


Figure 7: ***Behavior of Output during Recessions.*** *Average percentage change in real GDP after the start of financial (left) and nonfinancial (right) recessions at time t, differentiated by pre-recession trends in the top 1% income share and labor productivity.*

If recessions are preceded by above average changes in top income inequality, then output declines more strongly compared with recessions that are characterized by below average changes in top income inequality during the prior expansion. Similarly, output also falls more strongly during recessions that are preceded by unusually low productivity growth, compared with the ones associated with above average productivity growth. Hence, pre-recession trends in top income inequality and productivity seem to affect the severity of recessions. However, other factors might be correlated with these pre-recession trends that would in fact determine the variation shown in Figure 7. In a next step, I therefore control for a range of other variables and also test for the statistical difference in these estimates. In addition, I consider $\xi^F_{k,t}$ and $\xi^N_{k,t}$ as continuous variables instead of differentiating based on their positive and negative realizations. To this end, I use the local projection approach by Jordà (2005).

[35] An expansion is defined as the period from the previous trough to the peak at time t based on local minima and maxima in real GDP (see Section 2.1 for a description).

4.1 Local Projections

Denote (log) real GDP in country k at time t by $y_{k,t}$ and consider the set of regressions

$$y_{k,t+h} - y_{k,t} = \Gamma_1^h X_{k,t} + \Gamma_2^h X_{k,t-1} + \beta_F^h F_{k,t} + \beta_N^h N_{k,t} \\ + \gamma_F^h F_{k,t} \cdot \xi_{k,t}^F + \gamma_N^h N_{k,t} \cdot \xi_{k,t}^N + u_{k,t}^h \quad \text{for } h = 1, \ldots, 5 \ , \tag{2}$$

where the dependent variable gives the percentage change in output from time t to $t+h$ and $X_{k,t}$ is a vector of controls. In $X_{k,t}$, I include the annual percentage changes in real GDP, investment, and aggregate credit from $t-1$ to t, as well as inflation and the current account at time t. Since Romer and Romer (2017b) find that monetary and fiscal space matters for the aftermath of crises, I also add nominal short- and long-term interest rates and the public debt-to-GDP ratio at time t.[36]

$F_{k,t}$ and $N_{k,t}$ are binary variables indicating the beginning of financial and nonfinancial recessions as defined in Section 2.1. The coefficients β_F^h and β_N^h therefore give the estimated percentage change in output h years after the start of a financial or a nonfinancial recession.

The additional effect of the buildup period on the response of output is captured by the interaction terms $F_{k,t} \cdot \xi_{k,t}^F$ and $N_{k,t} \cdot \xi_{k,t}^N$. The variables $\xi_{k,t}^F$ and $\xi_{k,t}^N$ follow their definitions above. The estimated percentage change of output after the start of a financial recession that was also preceded by a one-standard-deviation annual change in Z above its mean during the previous expansion is then given by $\beta_F^h + \gamma_F^h$ at horizon h; similarly, $\beta_N^h + \gamma_N^h$ for nonfinancial recessions.

Due to the differences in the availability of data, I again obtain evidence for top income inequality and productivity separately. In particular, I consider excess changes in the top 1% income share and labor productivity growth. The estimation results are given in Tables 6 and 7. Figure 8 summarizes the findings graphically, showing the percentage changes of output after the start of financial and nonfinancial recessions.

The left graph shows the estimation results for which the top 1% income share takes the place of variable Z; the right graph for which Z is given by (log) labor productivity. Comparing the red solid lines with the blue dotted-dashed lines, a well-known finding is confirmed: Financial recessions are typically more severe than nonfinancial recessions. Tables 6 and 7 also show that these differences are highly statistically significant. Tests regarding the equality of the coefficients $\hat{\beta}_N^h$ and $\hat{\beta}_F^h$ are rejected for conventional confidence levels, in particular beyond the first year after the start of a recession.

[36] All control variables are normalized to mean zero and standard deviation one for each respective sample. I did not find that the inclusion of country-fixed effects changed the results.

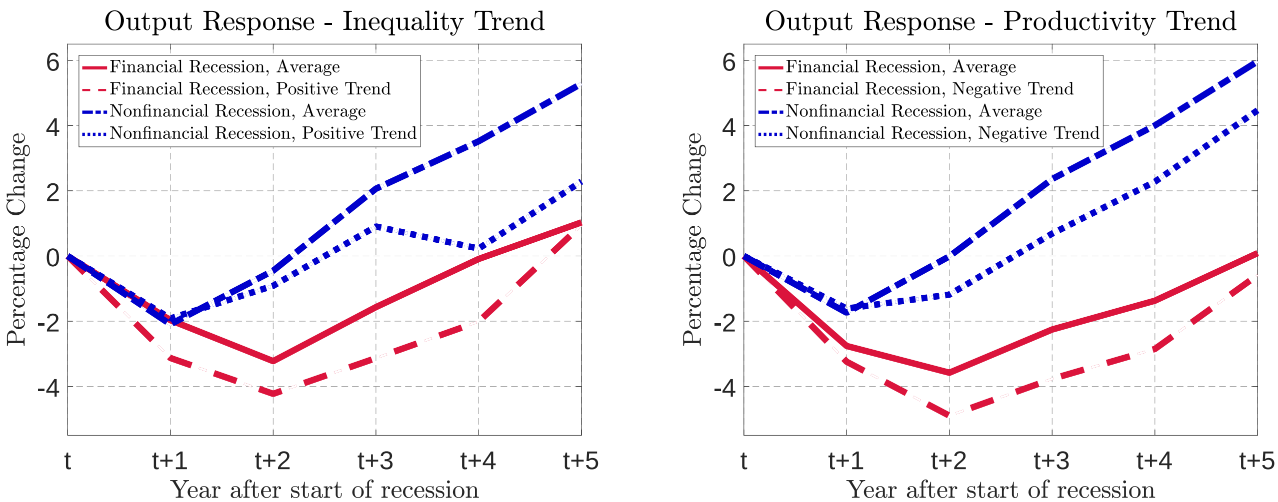


Figure 8: ***Behavior of Output during Financial and Nonfinancial Recessions.*** *Percentage changes in real GDP after start of financial (red) and nonfinancial (blue) recessions. Blue dotted lines and red dashed lines show recessions that were additionally preceded by an increase in top income inequality (left graph, 1.5 standard deviation above mean) or low productivity growth (right graph, 1.5 standard deviation below mean).*

The novel results are illustrated by the blue dotted and the red dashed lines. Financial and nonfinancial recessions that occur after excess increases in top income inequality or low productivity growth are associated with stronger declines in output. Tables 6 and 7 show that these differences − given by the coefficients $\hat{\gamma}_N^h$ and $\hat{\gamma}_F^h$ − are again statistically significant at standard confidence levels, though not for every horizon h. Thus, the results show that changes in top income inequality and productivity growth are informative not only about the likelihood of financial crises but also the severity of recessions, even when controlling for a range of other macroeconomic and financial factors.

To understand in more detail the behavior of output during recessions, I estimate again the set of regressions in (2), but instead of output as a dependent variable, I consider its subcomponents, consumption and investment. Figure 14 in Appendix A.3.1 shows the new set of responses. Financial and nonfinancial recessions that occur after excess increases in top income inequality or unusually low productivity growth are not only characterized by stronger declines in output but also by larger decreases in both consumption and investment.[37]

Robustness. Next, I again check for the robustness of the results. In particular, pre-recession credit booms are found to have lasting effects on the subsequent recovery periods (Jordà et al., 2013). I therefore additionally control for such pre-crisis trends in (2) by including interaction terms between excess credit changes − defined analogously to $\zeta_{k,t}^N$ and $\zeta_{k,t}^F$ − and financial and nonfinancial recession indicators, respectively. The new set of responses are shown in Figure 15 in Appendix A.3.2. The conclusions remain largely unchanged.

[37] Tables 29, 30, 31, and 32 in Appendix A.3.1 give the associated estimation results. While the differences between financial and nonfinancial recessions are generally statistically significant for standard confidence levels, that is not always the case for the partial effect of the pre-recession trends.

Year: h		1	2	3	4	5
Financial Recession ($F_{k,t}$)	$\hat{\beta}^h_F$	-1.969***	-3.225***	-1.568	-0.091	1.031
		(0.496)	(0.843)	(1.247)	(1.373)	(1.432)
Nonfinancial Recession ($N_{k,t}$)	$\hat{\beta}^h_N$	-2.095***	-0.450	2.065**	3.519***	5.286***
		(0.328)	(0.557)	(0.823)	(0.906)	(0.945)
Excess Income Share Top 1% ($\xi^F_{k,t}$) x ($F_{k,t}$)	$\hat{\gamma}^h_F$	-0.774**	-0.669	-1.043	-1.281	-0.056
		(0.309)	(0.525)	(0.776)	(0.854)	(0.891)
Excess Income Share Top 1% ($\xi^N_{k,t}$) x ($N_{k,t}$)	$\hat{\gamma}^h_N$	0.120	-0.309*	-0.773**	-2.194**	-2.001**
		(0.300)	(0.510)	(0.755)	(0.831)	(0.867)
$H\_0 : \hat{\beta}^h_N = \hat{\beta}^h_F$ (*p-value*)		0.846	0.014	0.029	0.048	0.026
Observations, Financial Recessions		26	26	26	26	26
Observations, Nonfinancial Recessions		52	52	52	52	52

Table 6: ***Behavior of GDP during Recessions - Pre-Recession Trends in the Top 1% Income Share.*** *Percentage change of GDP after the start of recessions. Notation: Standard errors in parentheses,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Year: h		1	2	3	4	5
Financial Recession ($F_{k,t}$)	$\hat{\beta}^h_F$	-2.760***	-3.581***	-2.256***	-1.372	0.088
		(0.369)	(0.614)	(0.817)	(1.104)	(1.179)
Nonfinancial Recession ($N_{k,t}$)	$\hat{\beta}^h_N$	-1.739***	-0.011	2.361***	4.004***	5.970***
		(0.227)	(0.378)	(0.503)	(0.680)	(0.725)
Excess LP ($\xi^F_{k,t}$) x ($F_{k,t}$)	$\hat{\gamma}^h_F$	0.322	0.879**	1.010**	0.987	0.448
		(0.220)	(0.367)	(0.487)	(0.659)	(0.703)
Excess LP ($\xi^N_{k,t}$) x ($N_{k,t}$)	$\hat{\gamma}^h_N$	-0.084	0.782*	1.116**	1.151	0.999
		(0.241)	(0.402)	(0.534)	(0.722)	(0.771)
$H\_0 : \hat{\beta}^h_N = \hat{\beta}^h_F$ (*p-value*)		0.029	0.000	0.000	0.000	0.000
Observations, Financial Recessions		48	48	48	48	48
Observations, Nonfinancial Recessions		111	111	111	111	111

Table 7: ***Behavior of GDP during Recessions - Pre-Recession Trends in Labor Productivity.*** *Percentage change of GDP after the start of recessions. Notation: Standard errors in parentheses,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

5 Conclusion

Rising top income inequality and low productivity growth are robust predictors of financial crises. Moreover, if crises are preceded by such developments, then output declines more strongly subsequently. These are the findings based on a long-run historical data set of macro-financial, productivity, and income inequality data for the vast majority of advanced economies. The relation between productivity growth and financial crises suggests that developments that originate in the real economy can drive financial instability. In contrast, I show that the predictive relation between top income inequality and financial crises is explained by asset booms.

Taken together with previous findings in the literature, financial crises tend to occur out of environments characterized by credit and asset price booms, external deficits, and low productivity growth. Overall, these results suggest that financial crises are not simply random events, but that they are typically preceded by a prolonged buildup of macro-financial imbalances. The findings can therefore provide a rationale for macro-prudential policies that aim to reduce the frequency and severity of financial crises by leaning against certain macroeconomic trends. Understanding the drivers of crises in the data further and matching the empirical patterns with macroeconomic models of financial crises (e.g., Paul, 2017) are exciting areas for future research.

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A Appendix

A.1 Data Description

Tables 8 and 9 use the following country abbreviations: AUS=Australia, BEL=Belgium, CAN=Canada, CHE=Switzerland, DEU=Germany, DNK=Denmark, ESP=Spain, FIN=Finland, FRA=France, GBR=Great Britain, ITA=Italy, JPN=Japan, NLD=Netherlands, NOR=Norway, PRT=Portugal, SWE=Sweden, USA=United States.

A.1.1 Macro-Financial Data

AUS	1893	1989							
BEL	1870	1885	1925	1931	1934	1939	2008		
CAN	1907								
CHE	1870	1910	1931	1991	2008				
DEU	1873	1891	1901	1907	1931	2008			
DNK	1877	1885	1908	1921	1931	1987	2008		
ESP	1883	1890	1913	1920	1924	1931	1977	2008	
FIN	1877	1900	1921	1931	1991				
FRA	1882	1889	1930	2008					
GBR	1890	1974	1991	2007					
ITA	1873	1887	1893	1907	1921	1930	1935	1990	2008
JPN	1871	1890	1907	1920	1927	1997			
NLD	1893	1907	1921	1939	2008				
NOR	1899	1922	1931	1988					
PRT	1890	1920	1923	1931	2008				
SWE	1878	1907	1922	1931	1991	2008			
USA	1873	1893	1907	1929	1984	2007			

Table 8: ***Financial Crises Dates.***

AUS	F	1891	1894	1989											
	N	1875	1878	1881	1883	1885	1887	1889	1896	1898	1900	1904	1910	1913	1926
		1938	1943	1951	1956	1961	1973	1976	1981	2008					
BEL	F	1870	1883	1926	1930	1937	2008								
	N	1872	1874	1887	1890	1900	1913	1916	1942	1951	1957	1974	1980	1992	
CAN	F	1907													
	N	1871	1874	1877	1882	1884	1888	1891	1894	1903	1913	1917	1928	1944	1947
		1953	1956	1981	1989	2008									
CHE	F	1871	1929	1990	2008										
	N	1875	1880	1886	1890	1893	1899	1902	1906	1912	1916	1920	1933	1939	1947
		1951	1957	1974	1981	1994	2001								
DEU	F	1875	1890	1908	1928	2008									
	N	1879	1898	1905	1913	1922	1943	1966	1974	1980	1992	2001			
DNK	F	1872	1876	1883	1920	1931	1987	2008							
	N	1870	1880	1887	1911	1914	1916	1923	1939	1944	1950	1962	1973	1979	1992
ESP	F	1883	1889	1913	1925	1929	1978	2007							
	N	1873	1877	1892	1894	1901	1909	1911	1916	1927	1932	1935	1940	1944	1947
		1952	1958	1974	1980	1992									
FIN	F	1876	1900	1929	1989										
	N	1870	1883	1890	1898	1907	1913	1916	1938	1941	1943	1952	1957	1975	2008
FRA	F	1882	1929	2007											
	N	1872	1874	1892	1894	1896	1900	1905	1907	1909	1912	1916	1920	1926	1933
		1937	1939	1942	1974	1992									
GBR	F	1873	1889	1973	1990	2007									
	N	1871	1875	1877	1883	1896	1899	1902	1907	1918	1925	1929	1938	1943	1951
		1957	1979												
ITA	F	1874	1887	1891	1929	1992	2007								
	N	1870	1883	1897	1918	1923	1925	1932	1939	1974	2002	2004			
JPN	F	1882	1901	1907	1913	1925	1997								
	N	1875	1877	1880	1887	1890	1892	1895	1898	1903	1919	1921	1929	1933	1940
		1973	2001	2007											
NLD	F	1892	1906	1937	1939	2008									
	N	1870	1873	1877	1889	1894	1899	1902	1913	1929	1957	1974	1980	2001	
NOR	F	1897	1920	1930	1987										
	N	1876	1881	1885	1893	1902	1916	1923	1939	1941	1957	1981	2007		
PRT	F	1890	1923	1929	2008										
	N	1870	1873	1877	1888	1893	1900	1904	1907	1912	1914	1916	1925	1927	1934
		1937	1939	1941	1944	1947	1951	1973	1982	1992	2002	2004			
SWE	F	1879	1907	1920	1930	1990	2007								
	N	1873	1876	1881	1883	1885	1888	1890	1899	1901	1904	1913	1916	1924	1939
		1976	1980												
USA	F	1873	1882	1892	1906	1929	2007								
	N	1875	1887	1889	1895	1901	1909	1913	1916	1918	1926	1937	1944	1948	1953
		1957	1969	1973	1979	1981	1990	2000							

Table 9: ***Business Cycle Peaks.*** *'F' denotes a financial recession, 'N' denotes a nonfinancial recession.*

A.1.2 Total Factor Productivity

Utilization-Adjustment I follow Imbs (1999) and adjust TFP for the utilization of the input factors. Following the notation in Section 2.3, consider the production function

$$Y_t = A_t \left(u_t K_t\right)^{\alpha} \left(e_t H_t\right)^{1-\alpha} \quad ,$$

where u_t and e_t denote capital utilization and labor effort, respectively. Using a partial equilibrium model of factor hoarding, Imbs (1999) shows how to obtain country-specific time series for u_t and e_t as functions of observables. In particular, these are given by

$$\begin{aligned} u_t &= \left(\frac{\frac{Y_t}{K_t}}{\frac{Y}{K}_{|ss}}\right)^{\frac{\delta}{\delta+r}} , \\ e_t &= \left(\alpha \frac{Y_t}{C_t}\right)^{\frac{1}{1+\psi}} \quad , \end{aligned}$$

where δ denotes the rate of depreciation (assumed to equal 0.1), r is the real interest rate (calibrated to 0.04), and $\frac{Y}{K}_{|ss}$ is the country-specific average output-to-capital ratio. C_t denotes real consumption and

$$\begin{aligned} \alpha &= 1 - \frac{K}{Y}_{|ss} \left(r + \delta\right) \quad , \\ \psi &= \frac{\alpha}{LS_{|ss}} - 1 \quad , \end{aligned}$$

where $\frac{K}{Y}_{|ss}$ is the country-specific average capital-to-output ratio and $LS_{|ss}$ is the country-specific average labor share. I collect the necessary data on private capital stocks from the IMF's Investment and Capital Stock data set, and on GDP, the labor share, the number of employed people, consumption, and average hours worked from the Penn World Table (Version 9.0). The utilization adjustment is derived by comparing the utilization-adjusted TFP with the unadjusted one. Since the data are only available from 1960 onward, I run country-specific regressions using the percentage change in total hours worked to predict the derived utilization adjustment. Based on the coefficients from this estimation, I use the predicted values for the whole sample to adjust the original TFP series by Bergeaud et al. (2016). As a robustness check, I compare the utilization adjustment for the United States to the one derived by Fernald (2014), who uses sector-specific data instead of economy-wide aggregates. The two series are highly correlated with a correlation coefficient of 0.79, both shown in Figure 9.

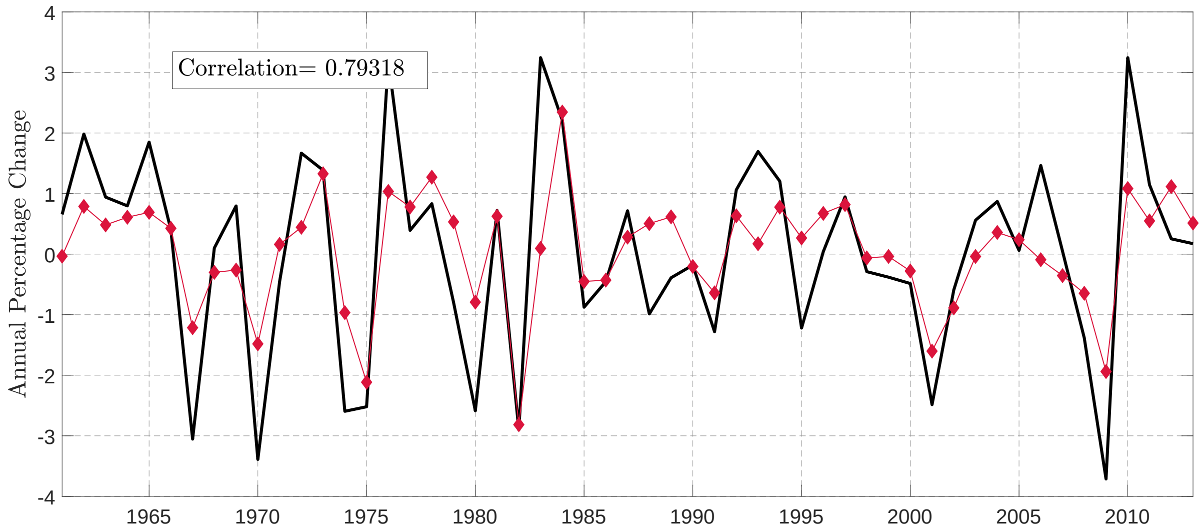

Figure 9: ***Comparison of utilization adjustment for the U.S.*** *Solid black series denotes the utilization adjustment by Fernald (2014) and red series with diamond markers denotes the utilization adjustment based on the approach by Imbs (1999).*

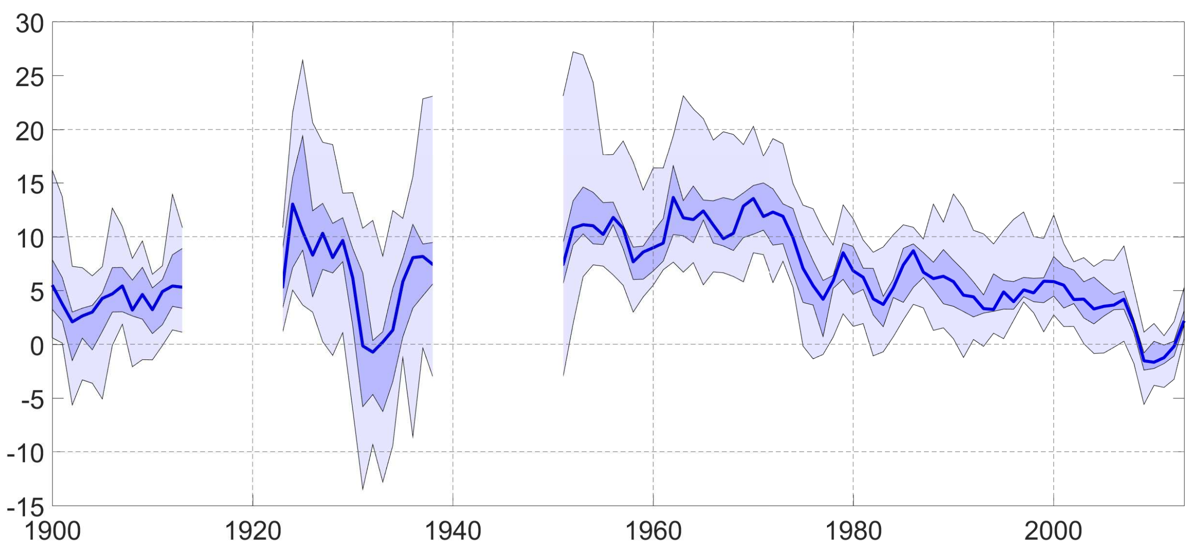

Figure 10: ***Four-Year TFP Growth.*** *Median, 33^{rd}, 66^{th}, 90^{th}, and 10^{th} percentiles shown.*

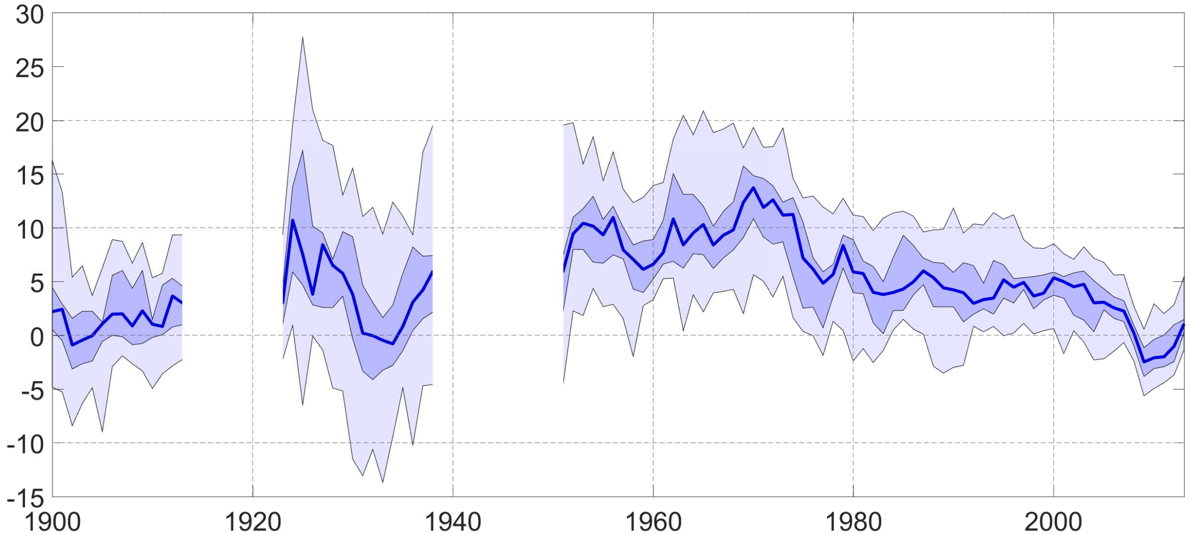

Figure 11: ***Four-Year Util.-adj. TFP Growth.*** *Median, 33^{rd}, 66^{th}, 90^{th}, and 10^{th} percentiles shown.*

A.2 Predicting Financial Crises − Additional Evidence

A.2.1 Income Inequality

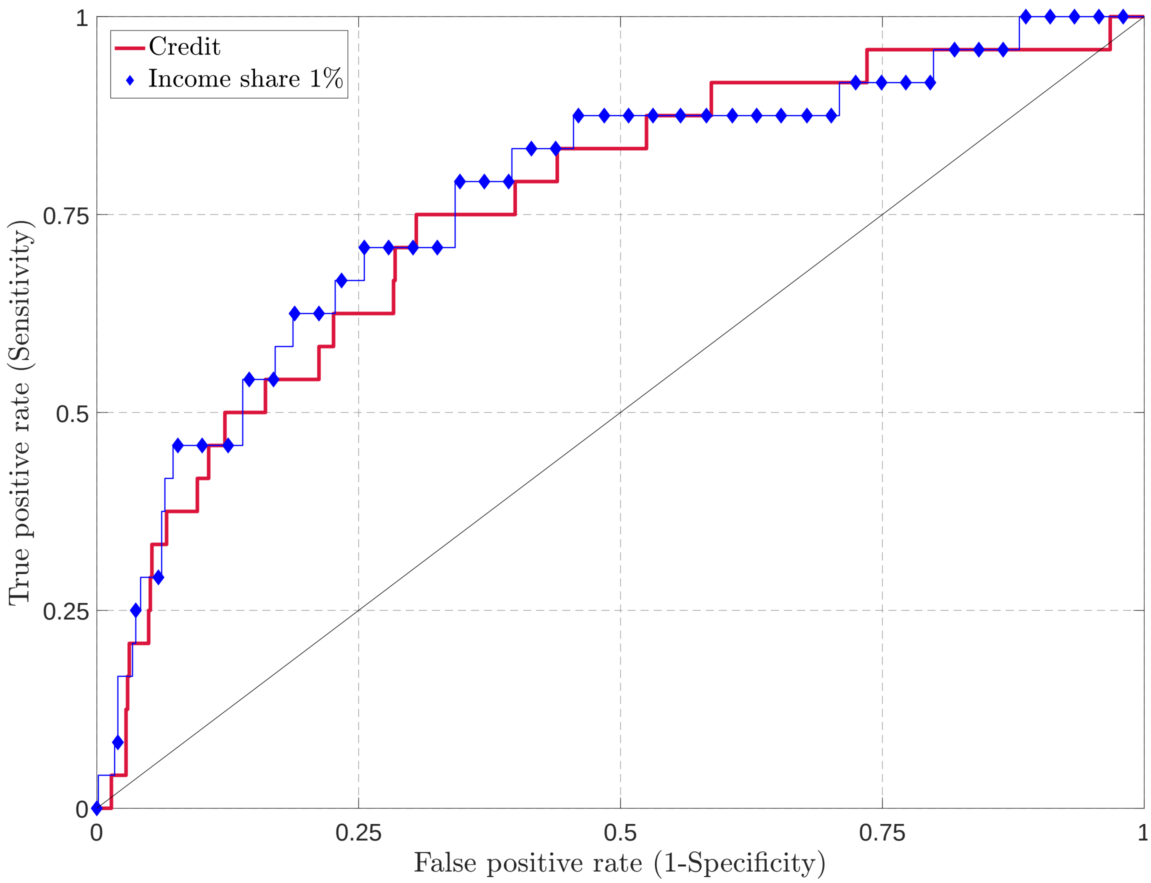

Figure 12: ***ROC Comparison.*** *Comparison of receiver operating characteristic curve for logistic probability models in columns 1 and 2 in Table 1. The area under the ROC is 0.758 for the model in column 1 (credit) and 0.772 for the model in column 2 (top 1% income share).*

	Baseline: Credit and income share 1% (logit)	Baseline no CFE: Credit and income share 1% (logit)	Credit and income share 1% (OLS)	Baseline Pre-WWII	Baseline Post-WWII	Baseline excluding Great Recession and Great Depression	Baseline predicting financial recessions	Baseline predicting nonfinancial recessions	Credit and log(income share 1%) (logit)	Demeaned by 20-year average
$\Delta_4\log(\text{Credit})_{t-1}$	0.512***	0.414***	0.017***	0.492*	0.686**	0.475*	0.540***	0.020	0.489***	0.332
	(0.192)	(0.128)	(0.006)	(0.271)	(0.324)	(0.279)	(0.184)	(0.110)	(0.186)	(0.236)
	[0.012]	[0.010]		[0.027]	[0.010]	[0.011]	[0.013]	[0.001]	[0.011]	[0.010]
$\Delta_4\text{Income Share 1\%}_{t-1}$	0.666***	0.608***	0.018***	0.505	0.817***	0.380*	0.753***	-0.109		0.412*
	(0.212)	(0.164)	(0.006)	(0.312)	(0.294)	(0.204)	(0.230)	(0.130)		(0.249)
	[0.015]	[0.015]		[0.028]	[0.012]	[0.008]	[0.018]	[-0.007]		[0.012]
$\Delta_4\log(\text{Income Share 1\%})_{t-1}$									0.695***	
									(0.198)	
									[0.016]	
Number of crises / recessions	29	29	29	9	20	16	31	68	29	19
Observations	814	903	903	127	657	527	814	903	814	459
Countries	14	16	16	7	14	10	14	16	14	13
Country FE	✓		✓	✓	✓	✓	✓	✓	✓	✓
p-value	0.940		0.025	0.997	0.916	0.895	0.910	0.527	0.884	0.584
Pseudo R^2	0.101	0.070	0.033	0.062	0.145	0.072	0.116	0.031	0.106	0.095
AUROC	0.779***	0.769***	0.799***	0.731***	0.812***	0.741***	0.806***	0.640***	0.785***	0.746***
	(0.044)	(0.037)	(0.037)	(0.085)	(0.058)	(0.062)	(0.036)	(0.034)	(0.041)	(0.061)

Table 10: ***Predicting Financial Crises.*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
$\Delta_4\log(\text{Credit})_{t-1}$	0.425*			0.465*	0.378
	(0.257)			(0.268)	(0.245)
	[0.011]			[0.009]	[0.009]
Δ_4Income Share $1\%_{t-1}$		0.824***		0.862***	
		(0.236)		(0.262)	
		[0.018]		[0.017]	
Δ_4Income Share $10\%_{t-1}$			0.662***		0.650***
			(0.226)		(0.230)
			[0.016]		[0.015]
Number of crises	25	25	25	25	25
Observations	701	701	701	701	701
Countries	14	14	14	14	14
Country FE	✓	✓	✓	✓	✓
p-value	0.595	0.718	0.761	0.683	0.746
Pseudo R^2	0.064	0.111	0.087	0.129	0.101
AUROC	0.708***	0.772***	0.738***	0.784***	0.763***
	(0.053)	(0.048)	(0.054)	(0.049)	(0.053)

Table 11: ***Predicting Financial Crises − Financial Crises by Reinhart and Rogoff (2009).*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
$\Delta_4\log(\text{Credit})_{t-1}$	0.913**			0.805**	0.808**
	(0.377)			(0.404)	(0.403)
	[0.022]			[0.016]	[0.016]
Δ_4Income Share $1\%_{t-1}$		0.753**		0.643**	
		(0.306)		(0.294)	
		[0.019]		[0.013]	
Δ_4Income Share $10\%_{t-1}$			0.781**		0.673**
			(0.329)		(0.312)
			[0.019]		[0.013]
Number of crises	14	14	14	14	14
Observations	399	399	399	399	399
Countries	12	12	12	12	12
Country FE	✓	✓	✓	✓	✓
p-value	0.750	0.997	0.996	0.891	0.910
Pseudo R^2	0.083	0.081	0.073	0.125	0.119
AUROC	0.726***	0.739***	0.711***	0.777***	0.765***
	(0.077)	(0.079)	(0.076)	(0.078)	(0.078)

Table 12: ***Predicting Financial Crises − Financial Crises Dates by Laeven and Valencia (2013).*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
$\Delta_4\log(\text{Credit})_{t-1}$	0.406			0.438	0.372
	(0.347)			(0.363)	(0.339)
	[0.011]			[0.009]	[0.009]
Δ_4Income Share $1\%_{t-1}$		0.629**		0.688**	
		(0.253)		(0.273)	
		[0.015]		[0.015]	
Δ_4Income Share $10\%_{t-1}$			0.293		0.267
			(0.232)		(0.235)
			[0.008]		[0.007]
Number of crises	14	14	14	14	14
Observations	471	471	471	471	471
Countries	11	11	11	11	11
Country FE	✓	✓	✓	✓	✓
p-value	0.997	0.999	1.000	0.995	0.998
Pseudo R^2	0.024	0.044	0.018	0.060	0.030
AUROC	0.636	0.698***	0.602	0.699***	0.653*
	(0.084)	(0.054)	(0.067)	(0.071)	(0.082)

Table 13: ***Predicting Financial Crises − Financial Crises Dates by Bordo et al. (2001).*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Any Financial Distress (>=1)

	(1)	(2)	(3)	(4)	(5)
$\Delta_4\log(\text{Credit})_{t-1}$	0.461*			0.398	0.406*
	(0.247)			(0.254)	(0.246)
	[0.017]			[0.013]	[0.013]
Δ_4Income Share $1\%_{t-1}$		0.559**		0.516**	
		(0.219)		(0.209)	
		[0.019]		[0.017]	
Δ_4Income Share $10\%_{t-1}$			0.602***		0.564***
			(0.201)		(0.193)
			[0.021]		[0.018]
Number of crises	25	25	25	25	25
Observations	533	533	533	533	533
Countries	15	15	15	15	15
Country FE	✓	✓	✓	✓	✓
p-value	0.299	0.906	0.888	0.589	0.568
Pseudo R^2	0.062	0.083	0.082	0.096	0.096
AUROC	0.694***	0.748***	0.734***	0.756***	0.748***
	(0.051)	(0.049)	(0.049)	(0.045)	(0.048)

Severe Financial Distress (>=7)

	(1)	(2)	(3)	(4)	(5)
$\Delta_4\log(\text{Credit})_{t-1}$	1.031***			0.945***	0.944***
	(0.320)			(0.327)	(0.319)
	[0.021]			[0.017]	[0.017]
Δ_4Income Share $1\%_{t-1}$		0.650**		0.539*	
		(0.326)		(0.300)	
		[0.016]		[0.010]	
Δ_4Income Share $10\%_{t-1}$			0.683**		0.584**
			(0.288)		(0.270)
			[0.017]		[0.010]
Number of crises	12	12	12	12	12
Observations	369	369	369	369	369
Countries	9	9	9	9	9
Country FE	✓	✓	✓	✓	✓
p-value	0.921	0.999	0.994	0.932	0.927
Pseudo R^2	0.089	0.065	0.060	0.126	0.124
AUROC	0.740***	0.733***	0.709***	0.793***	0.783***
	(0.067)	(0.083)	(0.068)	(0.062)	(0.064)

Table 14: ***Predicting Financial Crises − Financial Distress Measure by Romer and Romer (2017a).*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_4 \log(\text{Credit})_{t-1}$	0.833**	0.694**	0.813**	0.678**	0.896***	0.707**
	(0.339)	(0.335)	(0.340)	(0.334)	(0.301)	(0.299)
	[0.013]	[0.013]	[0.012]	[0.013]	[0.012]	[0.013]
Δ_4Income Share $1\%_{t-1}$	0.929***		0.942***		0.957***	
	(0.307)		(0.310)		(0.321)	
	[0.014]		[0.014]		[0.013]	
Δ_4Income Share $10\%_{t-1}$		0.714***		0.730***		0.710***
		(0.275)		(0.268)		(0.262)
		[0.014]		[0.014]		[0.013]
Number of crises	25	25	25	25	26	26
Observations	706	706	758	758	793	793
Countries	13	13	13	13	13	13
Country FE	✓	✓	✓	✓	✓	✓
p-value	0.733	0.856	0.929	0.953	0.827	0.917
Pseudo R^2	0.154	0.125	0.144	0.113	0.165	0.132
AUROC	0.822***	0.806***	0.816***	0.789***	0.824***	0.799***
	(0.048)	(0.046)	(0.048)	(0.046)	(0.047)	(0.045)

Table 15: ***Predicting Financial Crises - Linear Interpolation.*** *Results from logit regressions. Columns (1) & (2) interpolate over one-year gaps, columns (3) & (4) over one- and two-year gaps, columns (5) & (6) over one-, two-, and three-year gaps in the top income share series. Notation: robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)
$\Delta_4\log(\text{Total Capital Income})_{t-1}$	0.060	-0.053	-0.078
	(0.235)	(0.072)	(0.094)
	[0.001]	[-0.001]	[-0.001]
Δ_4Income Top 1%$_{t-1}$		0.704**	
		(0.294)	
		[0.015]	
Δ_4Income Top 1% Labor$_{t-1}$			-0.008
			(0.317)
			[-0.000]
Δ_4Income Top 1% Capital$_{t-1}$			1.048***
			(0.324)
			[0.013]
Number of crises	9	9	5
Observations	404	322	230
Countries	7	7	6
Country FE			
p-value			
Pseudo R^2	0.000	0.053	0.152
AUROC	0.511	0.698**	0.796***
	(0.101)	(0.090)	(0.087)

Table 16: ***Predicting Financial Crises - Total Capital Income.*** *Results from logit regressions. Columns (1) & (2) interpolate over one-year gaps, columns (3) & (4) over one- and two-year gaps, columns (5) & (6) over one-, two-, and three-year gaps in the top income share series. Notation: robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	GDP	Util.-adj. TFP	Labor Productivity	Short-term Nominal Interest rate	Long-term Nominal Interest rate	Short-term Real Interest rate	Inflation	Gov. Debt-to-GDP
Δ_4Income Share 1%$_{t-1}$	0.680***	0.666***	0.670***	0.739***	0.739***	0.740***	0.649***	0.661***
	(0.195)	(0.197)	(0.192)	(0.206)	(0.222)	(0.206)	(0.188)	(0.179)
	[0.018]	[0.018]	[0.017]	[0.018]	[0.019]	[0.018]	[0.017]	[0.017]
Number of crises	29	29	29	29	29	29	29	29
Observations	814	809	814	801	814	801	814	799
Countries	14	14	14	14	14	14	14	14
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
p-value	0.978	0.981	0.988	0.975	0.966	0.975	0.971	0.955
Pseudo R^2	0.070	0.072	0.079	0.088	0.076	0.088	0.070	0.078
AUROC	0.719***	0.713***	0.730***	0.723***	0.719***	0.723***	0.718***	0.732***
	(0.046)	(0.050)	(0.046)	(0.055)	(0.054)	(0.054)	(0.047)	(0.049)

Table 17: ***Predicting Financial Crises.*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Credit-to-GDP	Nonmortgage and Mortgage Credit	Firm and Household Credit	Investment-to-GDP	Current Account-to-GDP	Real House Prices	Real Stock Prices
Δ_4Income Share 1%$_{t-1}$	0.650***	0.745***	0.781***	0.575***	0.742***	0.659***	0.513**
	(0.237)	(0.196)	(0.278)	(0.179)	(0.190)	(0.204)	(0.202)
	[0.012]	[0.014]	[0.010]	[0.014]	[0.016]	[0.015]	[0.012]
Number of crises	29	28	20	29	29	28	28
Observations	811	792	589	810	810	782	801
Countries	14	14	14	14	14	14	14
Country FE	✓	✓	✓	✓	✓	✓	✓
p-value	0.640	0.872	0.460	0.963	0.903	0.922	0.914
Pseudo R^2	0.156	0.136	0.184	0.088	0.111	0.098	0.094
AUROC	0.813***	0.813***	0.840***	0.755***	0.791***	0.756***	0.761***
	(0.035)	(0.036)	(0.046)	(0.046)	(0.037)	(0.051)	(0.040)

Table 18: ***Predicting Financial Crises.*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

A.2.2 Wealth-to-Income Ratio

Δ_4Wealth$-$income Ratio$_{t-1}$	0.538**	0.345
	(0.235)	(0.277)
	[0.018]	[0.010]
$\Delta_4\log(\text{House Prices})^{\text{Real}}_{t-1}$		0.379*
		(0.208)
		[0.011]
$\Delta_4\log(\text{Stock Prices})^{\text{Real}}_{t-1}$		0.464**
		(0.189)
		[0.013]
Number of crises	28	28
Observations	700	700
Countries	12	12
Country FE	✓	✓
p-value	0.996	0.976
Pseudo R^2	0.044	0.080
AUROC	0.661***	0.729***
	(0.057)	(0.052)

Table 19: ***Predicting Financial Crises.*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

A.2.3 Productivity

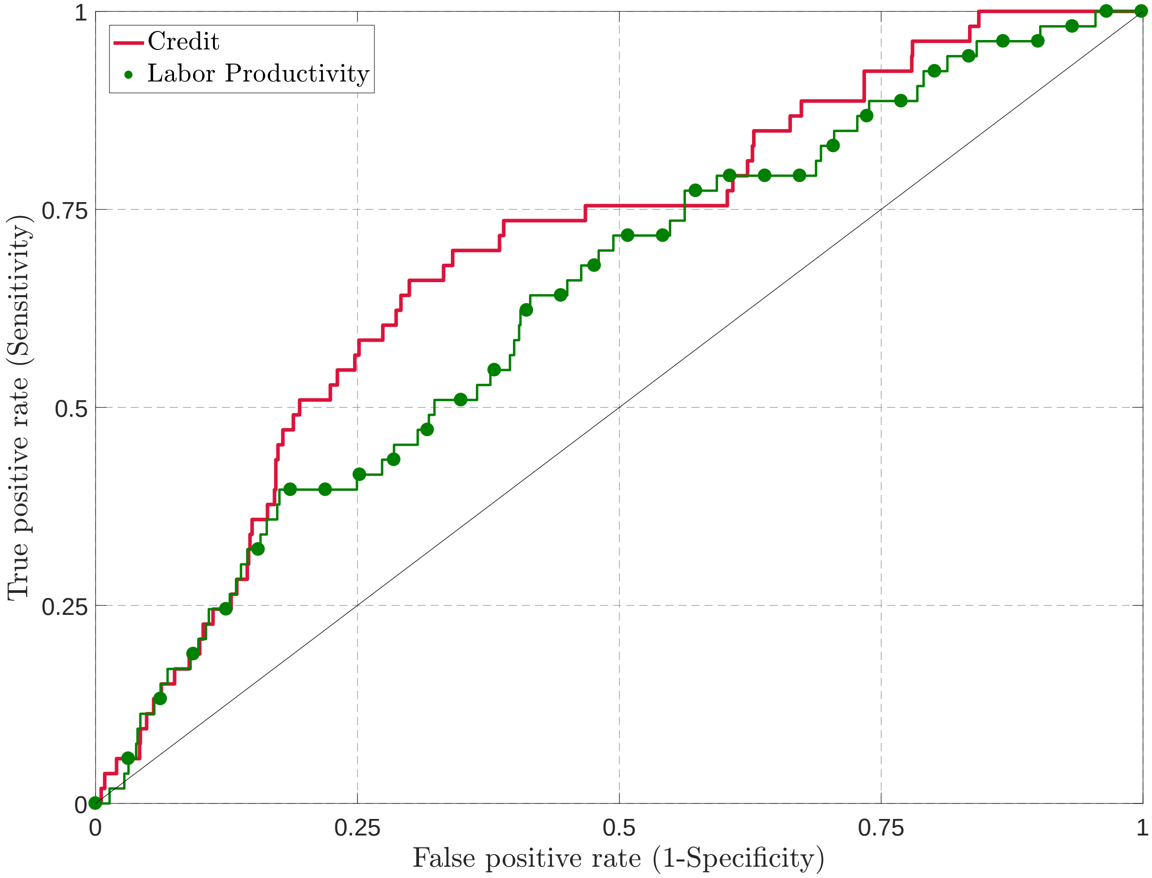

Figure 13: ***ROC Comparison.*** *Comparison of receiver operating characteristic curve for logistic probability models in columns 1 and 3 in Table 4. The area under the ROC is 0.695 for the model in column 1 (credit) and 0.636 for the model in column 3 (labor productivity).*

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_4\log(\text{Credit})_{t-1}$		0.425*			0.572**	0.700***
		(0.218)			(0.224)	(0.205)
		[0.009]			[0.010]	[0.011]
$\Delta_4\log(\text{TFP})_{t-1}^{\text{util.-adj.}}$			-0.549***		-0.699***	
			(0.181)		(0.185)	
			[-0.011]		[-0.012]	
$\Delta_4\log(\text{LP})_{t-1}$				-0.724***		-1.003***
				(0.199)		(0.252)
				[-0.013]		[-0.015]
Number of crises	24	24	24	24	24	24
Observations	974	974	974	974	974	974
Countries	16	16	16	16	16	16
Country FE	✓	✓	✓	✓	✓	✓
p-value	0.998	0.996	1.000	1.000	0.998	0.998
Pseudo R^2	0.017	0.037	0.040	0.053	0.075	0.100
AUROC	0.604*	0.668***	0.679***	0.704***	0.732***	0.766***
	(0.055)	(0.063)	(0.045)	(0.041)	(0.050)	(0.042)

Table 20: ***Predicting Financial Crises − Post-WWII.*** *Results from logit regressions. Column (1) includes only country-fixed effects. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Baseline: Credit and LP (logit)	Baseline no CFE: Credit and LP (logit)	Credit and LP (OLS)	Baseline Pre-WWII	Baseline Post-WWII	Baseline excluding Great Recession and Great Depression	Baseline predicting financial recessions	Baseline predicting nonfinancial recessions	Credit and input factors	Demeaned by 20-year average
$\Delta_4\log(\text{Credit})_{t-1}$	0.364***	0.339***	0.020***	0.334***	0.700***	0.259**	0.326***	0.082	0.466***	0.601***
	(0.105)	(0.091)	(0.005)	(0.127)	(0.205)	(0.104)	(0.110)	(0.082)	(0.143)	(0.159)
	[0.011]	[0.011]		[0.016]	[0.011]	[0.006]	[0.009]	[0.007]	[0.013]	[0.017]
$\Delta_4\log(\text{LP})_{t-1}$	-0.352***	-0.290***	-0.014***	0.249	-1.003***	-0.468***	-0.283***	-0.119		-0.263*
	(0.101)	(0.083)	(0.004)	(0.151)	(0.252)	(0.118)	(0.096)	(0.092)		(0.152)
	[-0.010]	[-0.009]		[0.012]	[-0.015]	[-0.011]	[-0.008]	[-0.010]		[-0.007]
$\Delta_4\log(\text{Input Factors})_{t-1}$									-0.022	
									(0.158)	
									[-0.001]	
Number of crises / recessuib	63	63	63	39	24	38	60	172	53	46
Observations	1734	1734	1734	666	974	1327	1734	1734	1552	1235
Countries	17	17	17	16	16	15	17	17	17	17
Country FE	✓		✓	✓	✓	✓	✓	✓	✓	✓
p-value	0.890		0.321	0.910	0.998	0.977	0.959	0.465	0.962	0.951
Pseudo R^2	0.051	0.027	0.018	0.050	0.100	0.052	0.043	0.017	0.044	0.058
AUROC	0.705***	0.700***	0.727***	0.699***	0.766***	0.726***	0.692***	0.596***	0.695***	0.719***
	(0.032)	(0.030)	(0.029)	(0.040)	(0.042)	(0.040)	(0.032)	(0.023)	(0.035)	(0.038)

Table 21: ***Predicting Financial Crises.*** *Results from logit and ordinary least squares regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
$\Delta_4 \log(\text{Credit})_{t-1}$	0.197			0.251	0.284
	(0.209)			(0.216)	(0.223)
	[0.007]			[0.008]	[0.009]
$\Delta_4 \log(\text{TFP})_{t-1}^{\text{util.-adj.}}$		-0.205*		-0.265**	
		(0.115)		(0.125)	
		[-0.007]		[-0.009]	
$\Delta_4 \log(\text{LP})_{t-1}$			-0.213**		-0.305**
			(0.101)		(0.122)
			[-0.007]		[-0.010]
Number of crises	58	58	58	58	58
Observations	1500	1500	1500	1500	1500
Countries	17	17	17	17	17
Country FE	✓	✓	✓	✓	✓
p-value	0.989	0.988	0.985	0.984	0.981
Pseudo R^2	0.019	0.018	0.019	0.026	0.028
AUROC	0.623***	0.611***	0.612***	0.644***	0.652***
	(0.035)	(0.035)	(0.035)	(0.036)	(0.035)

Table 22: ***Predicting Financial Crises − Financial Crises Dates by Reinhart and Rogoff (2009).*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
$\Delta_4\log(\text{Credit})_{t-1}$	0.641**			0.716**	0.740**
	(0.285)			(0.287)	(0.294)
	[0.015]			[0.015]	[0.015]
$\Delta_4\log(\text{TFP})^{\text{util.-adj.}}_{t-1}$		-0.507***		-0.555***	
		(0.173)		(0.185)	
		[-0.012]		[-0.011]	
$\Delta_4\log(\text{LP})_{t-1}$			-0.546***		-0.615**
			(0.209)		(0.248)
			[-0.013]		[-0.012]
Number of crises	18	18	18	18	18
Observations	630	630	630	630	630
Countries	15	15	15	15	15
Country FE	✓	✓	✓	✓	✓
p-value	1.000	1.000	1.000	1.000	1.000
Pseudo R^2	0.046	0.033	0.033	0.073	0.077
AUROC	0.645**	0.670***	0.665***	0.703***	0.714***
	(0.074)	(0.049)	(0.049)	(0.064)	(0.063)

Table 23: ***Predicting Financial Crises − Financial Crises Dates by Laeven and Valencia (2013).*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
$\Delta_4\log(\text{Credit})_{t-1}$	0.453***			0.527***	0.607***
	(0.135)			(0.141)	(0.153)
	[0.012]			[0.013]	[0.014]
$\Delta_4\log(\text{TFP})_{t-1}^{\text{util.-adj.}}$		-0.170		-0.329**	
		(0.153)		(0.154)	
		[-0.005]		[-0.008]	
$\Delta_4\log(\text{LP})_{t-1}$			-0.276**		-0.502***
			(0.123)		(0.128)
			[-0.008]		[-0.012]
Number of crises	39	39	39	39	39
Observations	1212	1212	1212	1212	1212
Countries	16	16	16	16	16
Country FE	✓	✓	✓	✓	✓
p-value	0.944	0.960	0.938	0.889	0.836
Pseudo R^2	0.046	0.025	0.030	0.054	0.066
AUROC	0.699***	0.636***	0.652***	0.707***	0.728***
	(0.037)	(0.043)	(0.042)	(0.037)	(0.036)

Table 24: ***Predicting Financial Crises − Financial Crises Dates by Bordo et al. (2001).*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Any Financial Distress (>=1)

	(1)	(2)	(3)	(4)	(5)
$\Delta_4 \log(\text{Credit})_{t-1}$	0.226			0.399*	0.479**
	(0.195)			(0.205)	(0.207)
	[0.008]			[0.011]	[0.013]
$\Delta_4 \log(\text{TFP})^{\text{util.-adj.}}_{t-1}$		-0.708***		-0.776***	
		(0.155)		(0.154)	
		[-0.022]		[-0.022]	
$\Delta_4 \log(\text{LP})_{t-1}$			-0.812***		-0.925***
			(0.192)		(0.190)
			[-0.024]		[-0.025]
Number of crises	32	32	32	32	32
Observations	776	776	776	776	776
Countries	17	17	17	17	17
Country FE	✓	✓	✓	✓	✓
p-value	0.951	0.950	0.945	0.729	0.641
Pseudo R^2	0.028	0.064	0.069	0.076	0.086
AUROC	0.632***	0.719***	0.722***	0.741***	0.753***
	(0.046)	(0.040)	(0.040)	(0.036)	(0.036)

Severe Financial Distress (>=7)

	(1)	(2)	(3)	(4)	(5)
$\Delta_4 \log(\text{Credit})_{t-1}$	0.821***			0.911***	0.923***
	(0.307)			(0.289)	(0.318)
	[0.016]			[0.015]	[0.015]
$\Delta_4 \log(\text{TFP})^{\text{util.-adj.}}_{t-1}$		-0.590***		-0.684***	
		(0.185)		(0.184)	
		[-0.013]		[-0.011]	
$\Delta_4 \log(\text{LP})_{t-1}$			-0.698***		-0.788***
			(0.217)		(0.196)
			[-0.015]		[-0.013]
Number of crises	14	14	14	14	14
Observations	504	504	504	504	504
Countries	11	11	11	11	11
Country FE	✓	✓	✓	✓	✓
p-value	0.969	0.999	0.999	0.974	0.967
Pseudo R^2	0.063	0.042	0.046	0.104	0.110
AUROC	0.709***	0.685***	0.695***	0.792***	0.797***
	(0.067)	(0.064)	(0.062)	(0.048)	(0.049)

Table 25: ***Predicting Financial Crises − Financial Distress Measure by Romer and Romer (2017a).*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Short-term Nominal Interest rate	Long-term Nominal Interest rate	Short-term Real Interest rate	Credit-to-GDP	Nonmortgage and Mortgage Credit	Firm and Household Credit
$\Delta_4\log(\text{LP})_{t-1}$	-0.338***	-0.299***	-0.339***	-0.185*	-0.498***	-0.591***
	(0.105)	(0.102)	(0.106)	(0.101)	(0.105)	(0.186)
	[-0.011]	[-0.009]	[-0.011]	[-0.005]	[-0.012]	[-0.011]
Number of crises	65	69	65	63	58	27
Observations	1722	1880	1713	1730	1636	952
Countries	16	17	16	17	17	16
Country FE	✓	✓	✓	✓	✓	✓
p-value	0.973	0.904	0.973	0.872	0.905	0.996
Pseudo R^2	0.034	0.028	0.034	0.070	0.077	0.097
AUROC	0.674***	0.646***	0.674***	0.712***	0.739***	0.762***
	(0.035)	(0.033)	(0.035)	(0.032)	(0.030)	(0.040)

Table 26: ***Predicting Financial Crises.*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Inflation	Investment-to-GDP	Current Account-to-GDP	Real House Prices	Real Stocks Prices	Gov. Debt-to-GDP
$\Delta_4\log(\text{LP})_{t-1}$	-0.241**	-0.455***	-0.314***	-0.400***	-0.352***	-0.386***
	(0.098)	(0.112)	(0.106)	(0.153)	(0.106)	(0.111)
	[-0.007]	[-0.013]	[-0.009]	[-0.012]	[-0.010]	[-0.011]
Number of crises	69	66	66	50	59	63
Observations	1893	1791	1819	1361	1672	1774
Countries	17	17	17	16	17	17
Country FE	✓	✓	✓	✓	✓	✓
p-value	0.907	0.861	0.890	0.994	0.923	0.872
Pseudo R^2	0.029	0.057	0.042	0.042	0.043	0.042
AUROC	0.644***	0.711***	0.678***	0.700***	0.679***	0.682***
	(0.033)	(0.031)	(0.032)	(0.037)	(0.033)	(0.033)

Table 27: ***Predicting Financial Crises.*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

A.2.4 Horse Race

Δ_log(Credit)$_{t-1}$	0.456***			0.414***	0.551***	0.503***
	(0.130)			(0.128)	(0.146)	(0.137)
	[0.013]			[0.010]	[0.015]	[0.012]
Δ_Income Share 1%$_{t-1}$		0.629***		0.608***		0.604***
		(0.156)		(0.164)		(0.171)
		[0.017]		[0.015]		[0.014]
Δ_log(LP)$_{t-1}$			-0.221		-0.366***	-0.313***
			(0.136)		(0.133)	(0.119)
			[-0.007]		[-0.010]	[-0.007]
Number of crises	29	29	29	29	29	29
Observations	903	903	903	903	903	903
Countries	16	16	16	16	16	16
Country FE						
p-value						
Pseudo R^2	0.028	0.047	0.006	0.070	0.043	0.083
AUROC	0.676***	0.717***	0.585	0.769***	0.708***	0.765***
	(0.050)	(0.043)	(0.052)	(0.037)	(0.045)	(0.037)

Table 28: ***Predicting Financial Crises.*** *Results from logit regressions. Notation: Robust standard errors in parentheses, marginal effects at mean in square brackets, the p-value refers to a test on the joint significance of the country-fixed effects,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

A.3 Financial and Nonfinancial Recessions — Additional Evidence

A.3.1 Consumption and Investment

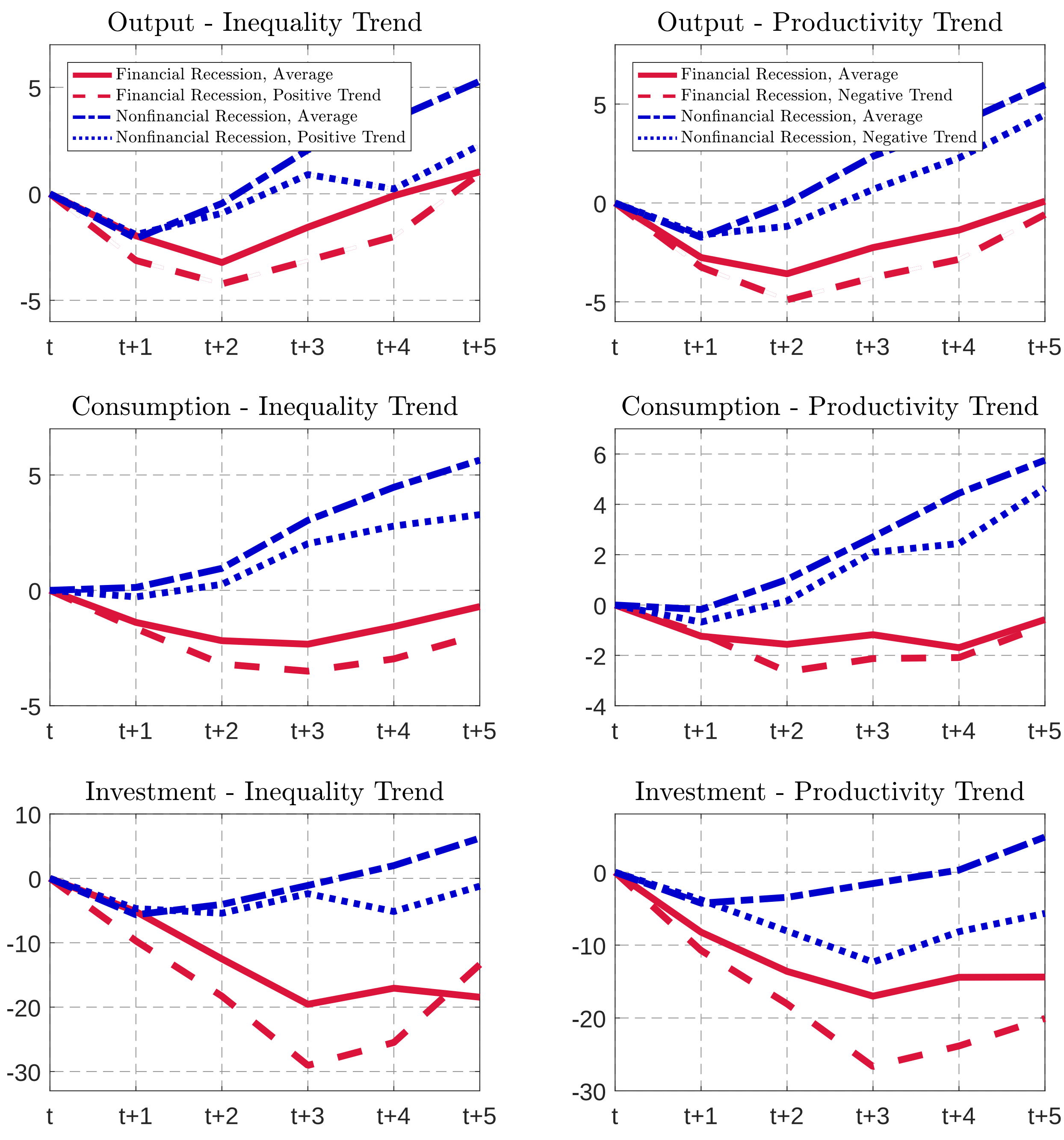

Figure 14: ***Behavior of Output during Financial and Nonfinancial Recessions.*** *Percentage changes in real GDP, consumption, and investment after start of financial (red) and nonfinancial (blue) recessions. Blue dotted lines and red dashed lines show recessions that were additionally preceded by an increase in the top 1% income share (left graph, 1.5 standard deviation above mean) or low labor productivity growth (right graph, 1.5 standard deviation below mean).*

Year: h		1	2	3	4	5
Financial Recession ($F_{k,t}$)	$\hat{\beta}^h_F$	-1.389***	-2.182***	-2.333**	-1.573	-0.703
		(0.424)	(0.681)	(1.032)	(1.229)	(1.304)
Nonfinancial Recession ($N_{k,t}$)	$\hat{\beta}^h_N$	0.126	0.953**	3.034***	4.468***	5.645***
		(0.280)	(0.450)	(0.681)	(0.811)	(0.861)
Excess Income Share Top 1% ($\xi^F_{k,t}$) x ($F_{k,t}$)	$\hat{\gamma}^h_F$	-0.178	-0.675	-0.779	-0.932	-0.807
		(0.264)	(0.424)	(0.642)	(0.764)	(0.811)
Excess Income Share Top 1% ($\xi^N_{k,t}$) x ($N_{k,t}$)	$\hat{\gamma}^h_N$	-0.273	-0.462*	-0.675	-1.121*	-1.576*
		(0.257)	(0.412)	(0.624)	(0.744)	(0.789)
$H\_0 : \hat{\beta}^h_N = \hat{\beta}^h_F$ (*p-value*)		0.008	0.001	0.000	0.000	0.000
Observations, Financial Recessions		26	26	26	26	26
Observations, Nonfinancial Recessions		52	52	52	52	52

Table 29: ***Behavior of Consumption during Recessions - Pre-Recession Trends in the Top 1% Income Share.*** *Percentage change of consumption after the start of recessions. Notation: Standard errors in parentheses,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Year: h		1	2	3	4	5
Financial Recession ($F_{k,t}$)	$\hat{\beta}^h_F$	-5.159*	-12.507***	-19.555**	-17.062**	-18.455***
		(2.820)	(4.241)	(7.381)	(7.052)	(6.390)
Nonfinancial Recession ($N_{k,t}$)	$\hat{\beta}^h_N$	-5.649***	-4.048	-1.105	1.984	6.243
		(1.861)	(2.799)	(4.871)	(4.654)	(4.217)
Excess Income Share Top 1% ($\xi^F_{k,t}$) x ($F_{k,t}$)	$\hat{\gamma}^h_F$	-3.038*	-3.859	-6.327	-5.619	3.383
		(1.754)	(2.638)	(4.591)	(4.386)	(3.974)
Excess Income Share Top 1% ($\xi^N_{k,t}$) x ($N_{k,t}$)	$\hat{\gamma}^h_N$	0.635	-0.912*	-0.848***	-4.757**	-4.971***
		(1.707)	(2.566)	(4.466)	(4.267)	(3.867)
$H\_0 : \hat{\beta}^h_N = \hat{\beta}^h_F$ (*p-value*)		0.894	0.131	0.060	0.042	0.004
Observations, Financial Recessions		26	26	26	26	26
Observations, Nonfinancial Recessions		52	52	52	52	52

Table 30: ***Behavior of Investment during Recessions - Pre-Recession Trends in the Top 1% Income Share.*** *Percentage change of investment after the start of recessions. Notation: Standard errors in parentheses,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Year: h		1	2	3	4	5
Financial Recession ($F_{k,t}$)	$\hat{\beta}_F^h$	-1.240***	-1.563***	-1.178*	-1.694	-0.578
		(0.336)	(0.518)	(0.706)	(1.143)	(1.322)
Nonfinancial Recession ($N_{k,t}$)	$\hat{\beta}_N^h$	-0.177	1.013***	2.707***	4.441***	5.753***
		(0.205)	(0.317)	(0.432)	(0.700)	(0.809)
Excess LP ($\xi_{k,t}^F$) x ($F_{k,t}$)	$\hat{\gamma}_F^h$	-0.073	0.725**	0.633	0.262	0.151
		(0.195)	(0.301)	(0.409)	(0.663)	(0.767)
Excess LP ($\xi_{k,t}^N$) x ($N_{k,t}$)	$\hat{\gamma}_N^h$	0.334	0.566*	0.410	1.333*	0.740
		(0.218)	(0.337)	(0.458)	(0.743)	(0.859)
$H\_0 : \hat{\beta}_N^h = \hat{\beta}_F^h$ (*p-value*)		0.012	0.000	0.000	0.000	0.000
Observations, Financial Recessions		46	46	46	46	46
Observations, Nonfinancial Recessions		108	108	108	108	108

Table 31: ***Behavior of Consumption during Recessions - Pre-Recession Trends in Labor Productivity.*** *Percentage change of consumption after the start of recessions. Notation: Standard errors in parentheses,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Year: h		1	2	3	4	5
Financial Recession ($F_{k,t}$)	$\hat{\beta}_F^h$	-8.223***	-13.603***	-17.002***	-14.415***	-14.383***
		(1.922)	(2.801)	(4.031)	(4.162)	(3.868)
Nonfinancial Recession ($N_{k,t}$)	$\hat{\beta}_N^h$	-4.241***	-3.442**	-1.542	0.301	4.837**
		(1.183)	(1.724)	(2.481)	(2.562)	(2.381)
Excess LP ($\xi_{k,t}^F$) x ($F_{k,t}$)	$\hat{\gamma}_F^h$	1.667	2.973*	6.440***	6.283**	3.785
		(1.147)	(1.671)	(2.405)	(2.483)	(2.308)
Excess LP ($\xi_{k,t}^N$) x ($N_{k,t}$)	$\hat{\gamma}_N^h$	-0.302	3.081*	7.194***	5.638**	6.989***
		(1.257)	(1.831)	(2.636)	(2.722)	(2.530)
$H\_0 : \hat{\beta}_N^h = \hat{\beta}_F^h$ (*p-value*)		0.100	0.004	0.003	0.005	0.000
Observations, Financial Recessions		48	48	48	48	48
Observations, Nonfinancial Recessions		111	111	111	111	111

Table 32: ***Behavior of Investment during Recessions - Pre-Recession Trends in Labor Productivity.*** *Percentage change of investment after the start of recessions. Notation: Standard errors in parentheses,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

A.3.2 Controlling for Pre-Recession Credit Booms

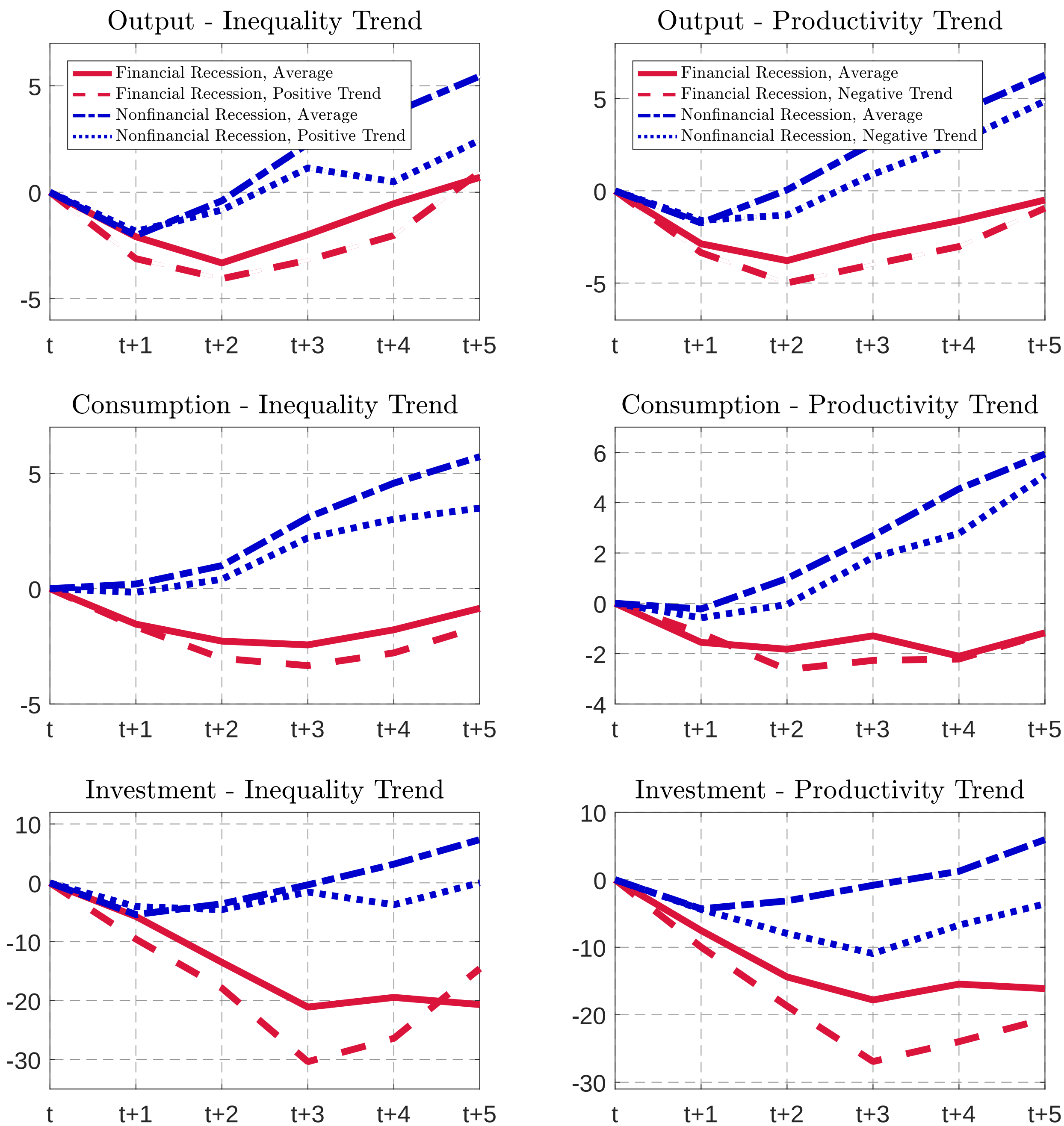

Figure 15: ***Behavior of Output during Financial and Nonfinancial Recessions - Controlling for Pre-Recession Trends in Credit.*** *Percentage changes in real GDP, consumption, and investment after start of financial (red) and nonfinancial (blue) recessions. Blue dotted lines and red dashed lines show recessions that were additionally preceded by an increase in the top 1% income share (left graph, 1.5 standard deviation above mean) or low labor productivity growth (right graph, 1.5 standard deviation below mean).*