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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. To this end, I assemble a novel data set of long-run measures of income inequality, productivity, and other macrofinancial indicators for advanced economies. I find that rising top income inequality and low productivity growth are robust predictors of crises, and their slow-moving trend components explain these relations. Moreover, recessions that are preceded by such developments are deeper than recessions without such ex-ante trends.

Keywords: Financial Crises, Productivity, Income Inequality

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

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"The underlying performance of the broader economy before the crisis was troubling as well. Productivity growth was slowing, wages were stagnating, and the share of Americans who were working was shrinking. That put pressure on family incomes even as inequality rose and upward social mobility declined. The desire to maintain relative living standards no doubt contributed to a surge in household borrowing before the crisis."

Bernanke, Geithner, and Paulson (2018)

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 macroeconomic determinants of crises, previous research has mainly focused on developments closely related to financial markets. For example, rapid growth in credit, stock prices, and house prices are found to be robust early-warning indicators of crises (e.g., Schularick and Taylor, 2012; Kiley, 2018). As I show in this paper, for each of these variables, it is the *cyclical component* that accounts for the predictive power based on cycle-trend decompositions at typical business cycle frequencies. Hence, the data speak towards the views of Kindleberger (1978) and Minsky (1986) that financial crises arise out of periods of speculative excesses and manias, associated with rapidly growing credit creation and asset prices.

In contrast to such temporary booms, the seeds of crises may also be sowed by *slow-moving and persistent trends* that originate in the real economy and that contribute towards a buildup of macrofinancial instability for many years. For example, as highlighted by the quote above, the U.S. economy experienced years of *rising income inequality* and *low productivity growth* leading up to the 2007-09 financial crisis (e.g., Piketty, Saez, and Zucman, 2016; Fernald, 2015). In this paper, I am interested in whether these 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 and collect several data sets to create a new composite set of long-run measures of income inequality, productivity, and other macrofinancial indicators. First, from the Macrohistory Database by Jordà, Schularick, and Taylor (2017b), I use several macrofinancial variables, such as aggregate credit measures, asset prices, and financial crises dates for 17 advanced economies from 1870 until 2013. Second, the Long-Term Productivity Database by Bergeaud, Cette, and Lecat (2016) provides measures of total factor productivity (TFP) and labor productivity (LP), covering the same set of countries with time series starting between 1870 and 1890 and available until 2013.

Third, from the World Inequality Database, I add data for the income shares of the top 1% and the top 10% of the income distribution. Among various measures of income inequality, these data have the longest coverage since they are based on historical tax income data. Nevertheless, the time series are available for fewer years than the productivity and the macrofinancial data. Moreover, when taking these data "off-the-shelf", the income shares for around half of the countries include capital gains, which are a part of the underlying tax income data. That is particularly problematic within the context of my paper, since capital gains induce substantial variation in the top income shares that is driven by asset price movements, as opposed to changes in the distribution of national income or aggregate output. To address this issue, I construct a new data set by carefully combining income inequality data that exclude capital gains from each of the country-specific sources.

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 macrofinancial 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 show that these predictive relations are explained by the *trend component* in each of the variables. That is, financial crises are typically preceded by slowly rising income inequality and years of low productivity growth. Third, I find that trends in top income inequality and productivity affect not only the likelihood of crises but also the recovery period. 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.

My findings have important implications for macrofinancial modeling. First, economies that experience prolonged periods of low productivity growth and rising income inequality may 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 macrofinance models need to reexamine how to model systemic risk by allowing for lower frequency fluctuations to influence financial instability. To the best of my knowledge, none of the current macrofinance models allow for such channels, but typically analyze the impact of transitory shocks on financial stability. In my view, this is a fruitful area for future research.

Related Literature. Morelli and Atkinson (2015) and Rajan (2010), among others, have noted the potential impact of changes in income inequality on financial crises. Kumhof, Rancière, and Winant (2015) have put forth a theoretical explanation for why this may be the case. All else being equal, after an increase in income inequality, wealthy individuals may lend their unused income to less wealthy individuals who can in turn support their own consumption. However, increased credit intermediation and the lower income of poorer households may raise the likelihood of default and the risk of a crisis.[1] Bordo and Meissner (2012) tested for this channel by estimating the response of credit to changes in income inequality and found no evidence.[2] However, Perugini et al. (2016) arrived at the opposite conclusion using a different sample and empirical specifications. Of course, both papers face the challenge of identifying truly exogenous changes of income inequality. Moreover, if income inequality is a systematic determinant of crises, then changes in income inequality should precede and predict crises. This is the idea in Kirschenmann, Malinen, and Nyberg (2016) and in this paper. Kirschenmann et al. (2016) show that changes in the top income shares contain relevant information to directly predict financial crises.

However, none of the mentioned papers excluded capital gains from the income inequality measures, and it is therefore unclear whether any of the previous findings − in favor or against a relation between income inequality and financial crises − are driven by asset price movements instead. As shown below, capital gains induce large and volatile changes of the top income shares that are not necessarily related to changes in the distribution of national income or aggregate output. Based on the income share data that I collected, I find that changes in the top income shares are still strong crises predictors, and I can exclude the possibility that these are simply asset price effects. The role of capital gains becomes evident for the trend-cycle decomposition. When capital gains are not excluded, then it is the cyclical part − and not the trend part − that explains the predictive power of the top income shares, driven by temporary asset price booms preceding crises.

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 shown below (Figure 5), across various countries, productivity growth is typically depressed around the outbreak of a crisis − either being the ultimate trigger of a crisis itself or the result of a trigger. 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 transitory 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 of positive shocks (e.g., Boissay, Collard, and Smets, 2016; Gorton and Ordoñez, 2016;

[1] Based on Kumhof et al. (2015), Cairó and Sim (2018) study the impact of monetary policy on financial stability.

[2] In a similar vein, Coibion, Gorodnichenko, Kudlyak, and Mondragon (2016) find that low-income households in high-inequality regions accumulated less debt over the period 2000-2012 than low-income households in low-inequality regions based on U.S. household-level data.

Paul, 2018).[3] However, the typical trigger of a crisis in these models is again an adverse shock.

In contrast to the behavior of productivity around the outbreak of a crisis, the empirical results show that low productivity growth typically precedes financial crises. In addition, I show that it is the trend component that accounts for this relation. Hence, years of low trend growth signal a financial crash in the near future.

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., Schularick and Taylor, 2012; Mueller, 2017), aggregate stock and house prices (e.g., Borio and Lowe, 2002; Anundsen, Gerdrup, Hansen, and Kragh-Sørensen, 2016; Kiley, 2018), and external deficits (e.g., Davis et al., 2016; Kiley, 2018).[4,5] With respect to the empirical setup, most papers consider simple (percentage) changes in the explanatory variables. A few papers have attempted to remove trend changes beforehand (e.g., Dell'Ariccia et al., 2016; Schularick, Richter, and Wachtel, 2017). I show that such a procedure is indeed justified for credit, asset prices, and the current account, since the cyclical component endows these variables with their predictive power. By contrast, for income inequality and productivity, the opposite is the case, and removing the trend would throw away valuable information. In this regard, the paper echoes the views by Comin and Gertler (2006).

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, and Jordà et al. (2013) obtain similar results with respect to pre-crisis credit booms.

Road Map. 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. Based on the results, Section 4 considers the decomposition into trend and cycle. Section 5 collects the results on the aftermath of financial crises. Section 6 concludes.

[3] 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.

[4] The focus of this paper is on the statistical predictive power of certain variables for the likelihood and severity of recessions 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).

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

2 Data

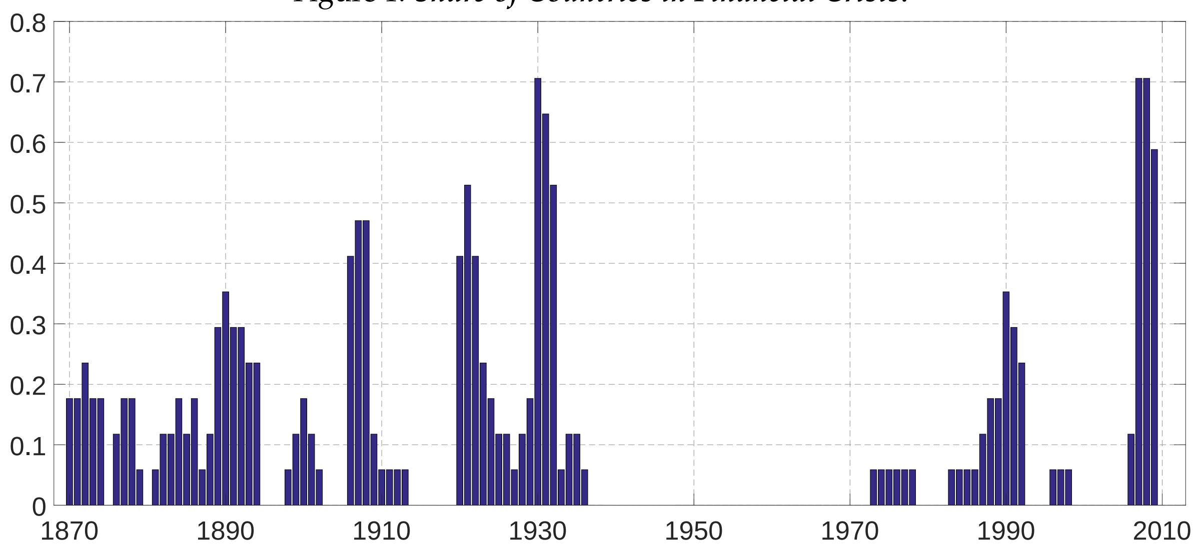
The data used for this analysis rely on three data sets that have been collected and made available recently. These are the Macrohistory Database, the Long-Term Productivity Database, and the World Inequality Database.[6]

2.1 Macro-Financial Data

The macro-financial data come from the Jorda-Schularick-Taylor Macrohistory Database (Jordà et al., 2017b). 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.[7] 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 9 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 1 summarizes these dates graphically by showing the three-year moving sum of the share of countries within a financial crisis.[8]

Figure 1: ***Share of Countries in Financial Crisis.***



Noticeable episodes are the Great Depression around 1930 and the Great Recession around 2008

[6]All three databases are publicly available (versions used are in parentheses): Macrohistory Database (release 2), World Inequality Database (August 2018), Long-Term Productivity Database (version 2.0).

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

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

– 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 (± 2 years), then the following recession is defined as a "financial recession". The remaining recessions are termed "nonfinancial recessions". Table 10 in Appendix A.1.1 lists all business cycle peaks.

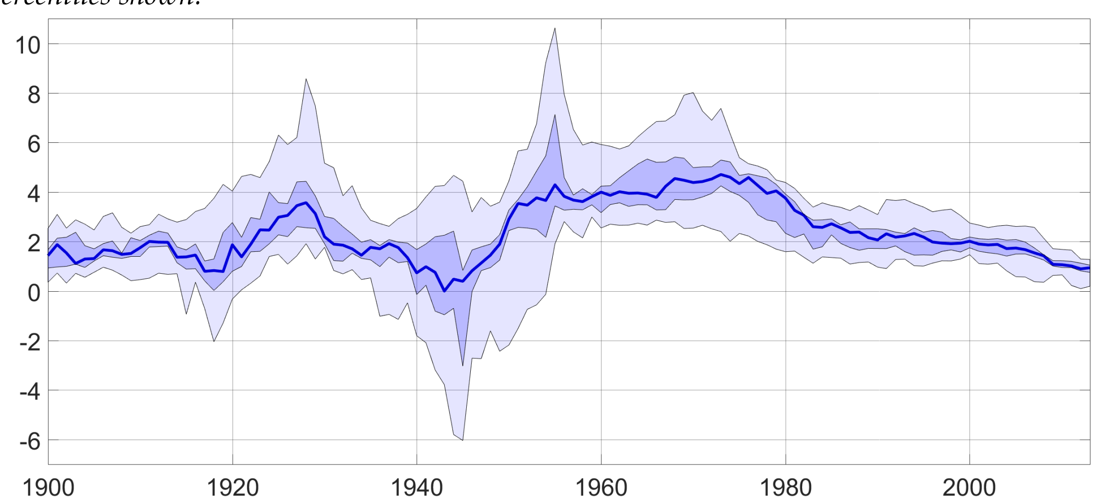
2.2 Productivity Data

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.[9] 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 2 shows how productivity growth has evolved over time, plotting percentiles in the distribution of the ten-year moving average labor productivity growth across all countries.[10]

Figure 2: ***Ten-Year Moving Average of Labor Productivity Growth.*** *Median, 33^{rd}, 66^{th}, 90^{th}, and 10^{th} percentiles shown.*



[9]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 $t-1$.

[10]The related figure for utilization-adjusted TFP is shown in Appendix A.1.2.

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 1). More recently, productivity growth has slowed down significantly. Overall, there is substantial cross-country heterogeneity throughout the sample.

2.3 Income Inequality Data

I use pretax income share data from the World Inequality 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, in particular tax income data.

An important issue that arises within the context of my paper is the treatment of realized capital gains that can be part of the income based on tax income data. Depending on the tax system in place, citizens may have to pay taxes on their revenues from selling certain assets. Using top income shares based on data that includes capital gains is potentially problematic since movements in asset prices can result in large fluctuations of such series (see also Burkhauser et al., 2015). Figure 3 illustrates this issue, showing the behavior of the top 1% income share with and without capital gains for Spain and the United States around the 2007-09 financial crisis.

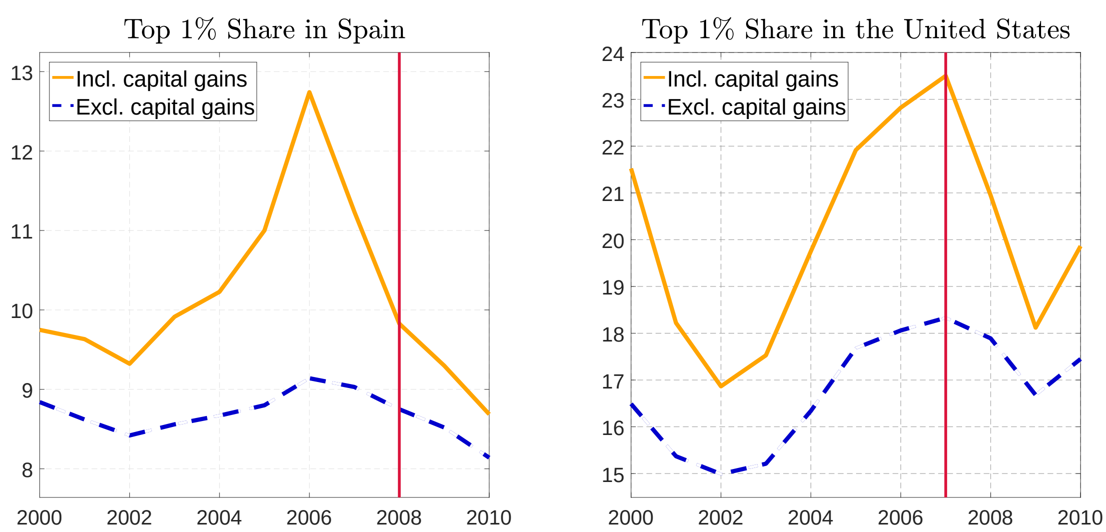


Figure 3: ***Top 1% income share with and without capital gains***. *Red vertical lines indicate the start of a financial crisis based on Jordà et al. (2017a). See Appendix B for details on the data sources.*

In Spain, the top 1% share that includes capital gains sharply rises between 2002 and 2006, whereas the movements are much smaller when capital gains are excluded from the income concept. For the United States, the top 1% share without capital gains rises substantially before 2007. However, in comparison, the top 1% share that includes capital gains still increases around twice as much between 2002 and 2007.

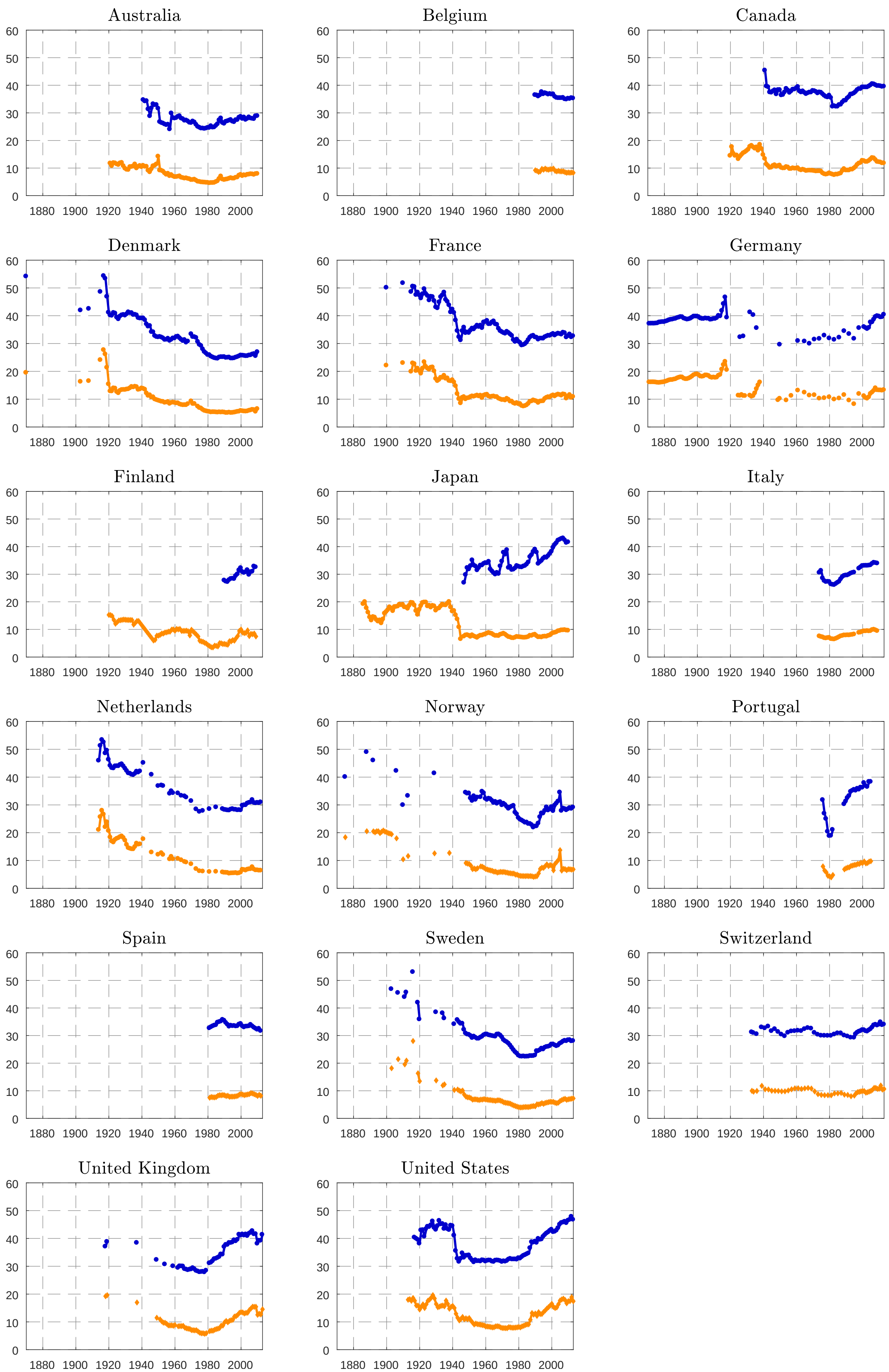


Figure 4: ***Income Shares of the Top 1% (bottom lines) and the Top 10% (upper lines).***

Since asset price booms tend to precede financial crises (Borio and Lowe, 2002; Kiley, 2018), the inclusion of capital gains could confound the relation between top income inequality and financial crises. Moreover, while revenues from selling assets constitute an income flow, they are not in fact tied to an economy's current production. From the perspective of national income and products accounting (NIPA), capital gains are not included because they "net-out" in the aggregate. For example, when one individual sells a house to another, it involves a transfer of assets and resources between people but not across sectors.

When taking the income share series "off-the-shelf" from the World Inequality Database, around half of the countries in the sample include capital gains.[11] Simply controlling for asset prices in the following regressions cannot resolve this issue. That is because taxes on capital gains vary across time and countries, often apply only to a subset of assets, and depend on the time when these assets were purchased.[12]

I therefore construct a new data set by adjusting the top income shares from the World Inequality Database to exclude capital gains.[13] The adjusted series are also in line with NIPA standards. The full description of the data is left to the Data Appendix B, including descriptions on important tax law changes. I am grateful to many researchers around the world who have shared their data with me and who have helped me put this data set together.

Figure 4 displays the resulting income share series for each country. I focus on the top 1% and the top 10% income shares since these series have the widest coverage. Noticeably, the inequality data are available for fewer years than the macrofinancial data. 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.

3 Predicting Financial Crises

Figure 5 shows the typical behavior of the key variables of interest around financial crises. 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.

[11] The top income share series largely overlap 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.

[12] For example, an increase in the number of transactions and a higher turnover of assets may already result in higher top income shares. That is because capital gains often only apply to assets that have been purchased in the recent past.

[13] For a few countries, it is not possible to separate out capital gains from the tax income data. For instance, capital gains may be reported together with other types of income. However, for the countries where that is the case, capital gains make up only a small fraction of overall income and are likely to introduce only a small bias (see Appendix B for details).

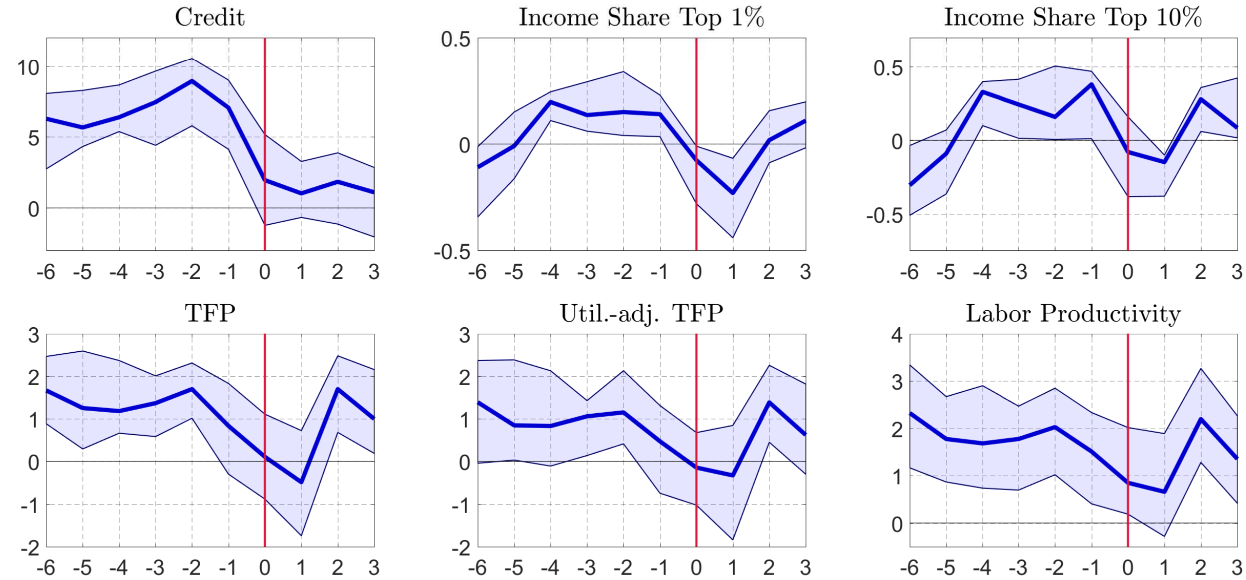


Figure 5: ***Annual (Percentage) Changes around Financial Crises.*** *Median, 33^{rd}, and 66^{th} percentiles.*

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 macrofinancial 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 financial crises dates in Jordà et al. (2017b). 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 and test the robustness of the results to slightly shorter or wider windows below. 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 three columns consider them jointly.

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 2−6 show that changes in top income shares are also statistically powerful predictors of crises. 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).[14] The income shares that include capital gains are even a more powerful predictor of crises as shown and further discussed in Section 4.

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_4\log(\text{Credit})_{t-1}$	0.811**			0.874**	0.740**	0.874**
	(0.342)			(0.375)	(0.355)	(0.392)
	[0.019]			[0.014]	[0.016]	[0.014]
Δ_4Income Share $1\%_{t-1}$		0.886***		0.919***		0.918***
		(0.258)		(0.279)		(0.272)
		[0.020]		[0.015]		[0.015]
Δ_4Income Share $10\%_{t-1}$			0.649***		0.611**	0.002
			(0.220)		(0.294)	(0.219)
			[0.017]		[0.013]	[0.000]
Number of crises	26	26	26	26	26	26
Observations	701	701	701	701	701	701
Countries	14	14	14	14	14	14
Country FE	✓	✓	✓	✓	✓	✓
p-value	0.598	0.903	0.890	0.739	0.870	0.751
Pseudo R^2	0.091	0.113	0.076	0.166	0.120	0.166
AUROC	0.764***	0.777***	0.741***	0.831***	0.813***	0.832***
	(0.050)	(0.050)	(0.048)	(0.046)	(0.044)	(0.046)

Table 1: ***Predicting Financial Crises.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Columns 4 and 5 show that the predictive power of the top income shares is preserved, though 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 2 percentage points in the probability that a crisis will occur within the next year (based on the esti-

[14] 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 11 in Appendix A.2.1.

mation results in column 2).[15] These effects can be considered substantial, given that the average frequency of crises is around 4% in the full sample.

Column 6 shows 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. Hence, capturing the income of earners at the very top of the income distribution is particularly important within the context of this paper.

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 given the findings from column 6 in Table 1. Starting from the regression in column 4 of Table 1, Table 11 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 95% confidence level, though smaller in magnitude. 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 the relation between income inequality and nonfinancial recessions is in fact negative.

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, I include additional data by linearly interpolating over small gaps in the income share series. Table 18 in Appendix A.2.1 shows the estimation for which one-, two-, and three-year gaps are filled. The results are much the same. In addition, I test whether the results are robust to using slightly shorter or wider windows for h in regression (1). Tables 12 and 13 in Appendix A.2.3 show the results for $h = 3$ and $h = 5$, which are again very similar to the baseline.

Next, I check whether the findings depend on the specific crises dates by Jordà et al. (2017b).[16] In Tables 14, 15, 16, and 17 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 (2009b) (available

[15]The standard-deviation of the top 1% share is 4.2%, so a sizable fraction of aggregate output.

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

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.[17] 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 2, 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, public debt to GDP, and aggregate credit.

	(1)	(2)	(3)
Δ_4Income Share 1%$_{t-1}$	0.707***	0.754***	0.826***
	(0.204)	(0.205)	(0.224)
	[0.011]	[0.011]	[0.008]
Set of controls	✓	✓	✓
GDP & Global GDP		✓	✓
Stock & House Prices			✓
Number of crises	31	31	29
Observations	813	813	769
Countries	15	15	15
Country FE	✓	✓	✓
p-value	0.755	0.818	0.313
Pseudo R^2	0.176	0.191	0.255
AUROC	0.821***	0.827***	0.868***
	(0.042)	(0.039)	(0.031)

Table 2: ***Predicting Financial Crises.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

In column 2, I also control for changes in domestic and global real GDP to proxy for worldwide trends.[18] 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

[17] In particular, 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.

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

1% income share still have predictive power for crises.[19,20]

Last, in the Data Appendix B, I document various tax law changes that may induce variation in the top income shares. For example, the top income shares can substantially jump or fall from one year to the next due to changes in the definition of the tax unit (e.g., United Kingdom 1989-1990) or because of changes in the tax code (e.g., Norway around 2006), which can, for example, lead to a sudden payout of dividends by firms (see e.g., Alstadsæter et al., 2017). While some of these tax law changes may actually be regarded as interesting natural experiments, I find that none of them drives the results in this paper when excluding the years around them.

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 2.2 and Appendix A.1.2. Table 3 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 22 in Appendix A.2.3).[21,22]

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

[19] In Tables 19 and 20 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.

[20] Based on data from the World Inequality Database, I also test for the predictive power of the national wealth-to-income ratio (see Table 21 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, the coefficient becomes indistinguishable from zero. Thus, the predictive power mainly arises from changes in asset prices. 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 Inequality Database contains wealth inequality data for only three out of the 17 countries in this paper. Even after adding 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.

[21] The associated curves for the results in columns 1 and 3 are plotted in Figure 12 in Appendix A.2.3.

[22] 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 3). 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 22 in Appendix A.2.3).

	(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]
$\Delta_4\log(\text{TFP})^{\text{util.-adj.}}_{t-1}$		-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 3: ***Predicting Financial Crises.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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 3 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 23 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. 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 2.2, does not have the same predictive power as productivity.

The results are also robust to using shorter or wider windows for h in regression (1) (see Tables 24 and 25 in Appendix A.2.3). Last, the findings also remain much the same when using the alternative financial crises dates by Reinhart and Rogoff (2009b), Laeven and Valencia (2013), Bordo et al. (2001), or Romer and Romer (2017a) (see Tables 26, 27, 28, and 29 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 4, I first include the same set of controls as in Table 2. Further, I add stock and house prices, and then the top 1% income share; both steps reduce the sample size.[23] Again, the predictive power of labor productivity remains intact.[24,25]

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 32 in Appendix A.2.4).[26] Inequality wins.

	(1)	(2)	(3)
$\Delta_4 \log(\mathrm{LP})_{t-1}$	-0.553***	-0.550**	-0.793**
	(0.134)	(0.216)	(0.355)
	[-0.012]	[-0.010]	[-0.008]
Set of controls	✓	✓	✓
Stock & House Prices		✓	✓
Income Share 1%			✓
Number of crises	53	41	29
Observations	1387	1145	769
Countries	16	16	15
Country FE	✓	✓	✓
p-value	0.849	0.782	0.132
Pseudo R^2	0.115	0.141	0.249
AUROC	0.756***	0.778***	0.857***
	(0.033)	(0.036)	(0.036)

Table 4: ***Predicting Financial Crises.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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

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

[25]Tables 30 and 31 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.

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

4 Trend vs. Cycle

The previous section has shown that changes in top income shares and percentage changes in productivity are robust early-warning indicators of crises. However, for simplicity, I did not distinguish whether these predictive relations are due to the cycle or the trend component within each variable. That is, do crises occur out of environments of persistently rising income inequality or years of low productivity growth, or because each of these variables temporarily deviates from their trend change?

To understand these differences, I decompose each variable into cyclical and trend changes for typical business cycle frequencies using a Hodrick-Prescott filter (HP filter).[27] The HP filter has been criticized on many grounds (e.g., Hamilton, 2018). Here, I simply use the filter to gain an understanding of the origins of the predictive relations in the data. I also find that the results below are not specific to the HP filter. For example, a band-pass filter gives very similar results.[28] However, a challenge remains to distinguish between temporary booms and trend changes in real time, an issue that I return to below.

The results are given in Table 5. For each variable, I show the estimation results based on regression (1) (without additional regressors) and its decomposition into trend and cycle. The first four columns show that the negative relation between productivity and financial crises is due to the trend component. While the cyclical part of labor productivity is also statistically different from zero at the 90% confidence level, the coefficient in fact has a positive sign.

Turning to income inequality, I consider both the constructed measure for the top 1% income share that excludes capital gains as well as the shares that take into account capital gains for around half of the countries. Comparing columns 5 and 7, the magnitude of the estimated relation is slightly larger when capital gains are not excluded, which is likely due to the additional impact from asset prices.

Moreover, when decomposing each of the measures into cycle and trend, capital gains again play an important role. If they are excluded, it is the trend component that has the statistically significant coefficient. By contrast, if capital gains are not excluded, it is the cyclical part that explains the predictive relation. For some alternative specifications (see footnotes 27 and 28), I found that the cyclical component for the top income shares without capital gains is also statistically significant at standard confidence levels, suggesting that a medium-term cycle might best represent the predictive power.

[27] In particular, I decompose the four-year differences of each regressor in regression (1). I find that the results are similar when decomposing each variable either in (log-)levels or first-differences and subsequently computing four-year (percentage) changes for trend and cycle.

[28] More specifically, I find that the results are much the same when using a Baxter-King filter that associates the cycle with frequencies between two and eight years, i.e., conventional business cycle frequencies (see, e.g., Comin and Gertler, 2006).

	Labor Productivity		Util.-adj. TFP		Top1% Share		Top1% Share Cap. Gains	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_4(.)_{t-1}$	-0.281***		-0.224*		0.683***		0.788***	
	(0.088)		(0.134)		(0.224)		(0.265)	
	[-0.009]		[-0.006]		[0.019]		[0.021]	
Cycle		0.203*		0.259		0.512		0.625**
		(0.116)		(0.162)		(0.339)		(0.301)
		[0.006]		[0.007]		[0.014]		[0.016]
Trend		-0.441***		-0.400***		0.313*		0.293
		(0.099)		(0.109)		(0.166)		(0.206)
		[-0.013]		[-0.011]		[0.009]		[0.008]
Number of crises	69	69	53	53	31	31	31	31
Observations	1892	1892	1597	1597	808	808	809	809
Countries	17	17	17	17	15	15	15	15
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
p-value	0.000	0.000	0.001	0.000	0.168	0.434	0.137	0.000
Pseudo R^2	0.027	0.039	0.022	0.037	0.074	0.081	0.088	0.097
AUROC	0.644***	0.673***	0.629***	0.674***	0.718***	0.737***	0.729***	0.750***
	(0.033)	(0.029)	(0.040)	(0.035)	(0.047)	(0.049)	(0.045)	(0.048)

Table 5: ***Predicting Financial Crises.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. HP filter used for decomposition with smoothing parameter $\lambda = 6.25$ based on Ravn and Uhlig (2002). 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, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.*

To understand whether asset prices can account for the differences between the two top income share series, I repeat the exercise in Table 5 for stock and house prices. In addition, I also consider credit and the current account which have been shown to be strong crisis predictors (e.g., Schularick and Taylor, 2012; Kiley, 2018).[29] Table 6 shows the results. In contrast to productivity and income inequality, it is the cyclical component for these variables that accounts for the relations in the data and explains the same result for the top 1% share that includes capital gains. The trend component of stock prices is also statistically different from zero at the 99% confidence level, but the coefficient is in fact negative, as opposed to the estimated coefficient in the first column which has a positive sign.

Overall, these results confirm the intuition that temporary booms in credit and asset prices, as well as a worsening of the current account, typically precede crises. In contrast, years of rising income inequality and persistently low productivity growth also sow the seeds for a crisis.

[29] More specifically, I consider real stock prices, real house prices, and real credit (all in logs), as well as the current account to GDP.

	Stock Prices		House Prices		Credit		Current Account	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_4(.)_{t-1}$	0.317***		0.278*		0.309**		-0.338**	
	(0.097)		(0.145)		(0.137)		(0.158)	
	[0.010]		[0.009]		[0.010]		[-0.011]	
Cycle		0.758***		0.529***		0.561***		-0.266**
		(0.129)		(0.157)		(0.116)		(0.121)
		[0.019]		[0.016]		[0.016]		[-0.008]
Trend		-0.267***		0.018		-0.029		-0.157
		(0.092)		(0.093)		(0.186)		(0.152)
		[-0.007]		[0.001]		[-0.001]		[-0.005]
Number of crises	60	60	51	51	65	65	68	68
Observations	1689	1689	1385	1385	1777	1777	1863	1863
Countries	17	17	16	16	17	17	17	17
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
p-value	0.000	0.000	0.000	0.000	0.346	0.000	0.000	0.000
Pseudo R^2	0.028	0.078	0.024	0.043	0.035	0.060	0.027	0.027
AUROC	0.639***	0.714***	0.652***	0.667***	0.672***	0.715***	0.639***	0.638***
	(0.033)	(0.034)	(0.041)	(0.043)	(0.033)	(0.032)	(0.033)	(0.032)

Table 6: ***Predicting Financial Crises.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. HP filter used for decomposition with smoothing parameter $\lambda = 6.25$ based on Ravn and Uhlig (2002). 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, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.*

For the decomposition into trend and cycle in Tables 5 and 6, I have relied on post-crisis data, and therefore on information that is not available in real time. Hamilton (2018) proposes an alternative to the HP filter to estimate a trend in real time.[30] Based on this method, the results are shown in Tables 33 and 34 in Appendix A.3. In contrast to the previous results, both trend and cycle for each respective variable now have predictive power and are of the same sign. Thus, these findings show that the challenge to distinguish between trend and cycle in real time remains.

5 Severity of Recessions

The results thus far show that both movements in top income inequality and productivity growth have predictive power with respect to the likelihood of financial crises. Next, I study whether these variables are also informative about the severity of recessions. To increase the number of observations, I consider all types of recessions and later distinguish between financial and nonfinancial recessions. Based on the recession dates defined in Section 2.1, Figure 6 illustrates that the

[30] In particular, Hamilton (2018) suggests to predict a trend at time t of some variable y_t in (log-)levels based on an OLS regression with four lags, $y_t = \hat{\alpha} + \hat{\beta}_1 y_{t-k} + \hat{\beta}_2 y_{t-k-1} + \hat{\beta}_3 y_{t-k-2} + \hat{\beta}_4 y_{t-k-3}$. For the macro-financial data by Jordà et al. (2017b), he explicitly suggests to consider $k = 5$. After estimating trend and cycle in (log-)levels, I take again four-year-differences to match the specification in (1).

response of output varies greatly across countries and periods during recessions. Some countries experience prolonged spells of depressed output, while others recover relatively quickly.

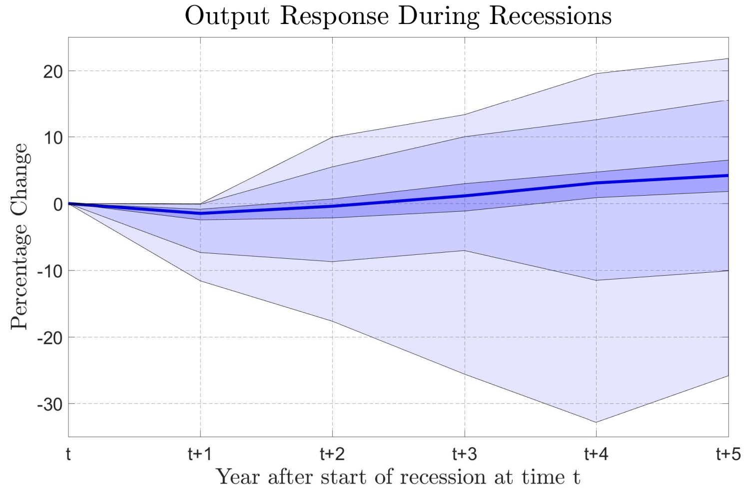


Figure 6: ***Behavior of Output during Recessions.*** *Percentage change in real GDP after the start of recessions. Median, 33rd and 66th, 5th and 95th, 1st and 99th percentiles are shown.*

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 either high or low growth in top income inequality or productivity. In particular, I consider the average percentage change in real GDP after the start of a recession that was preceded by changes in the top 1% income share or labor productivity growth more than one-standard-deviation above (or below) average over the three preceding years.

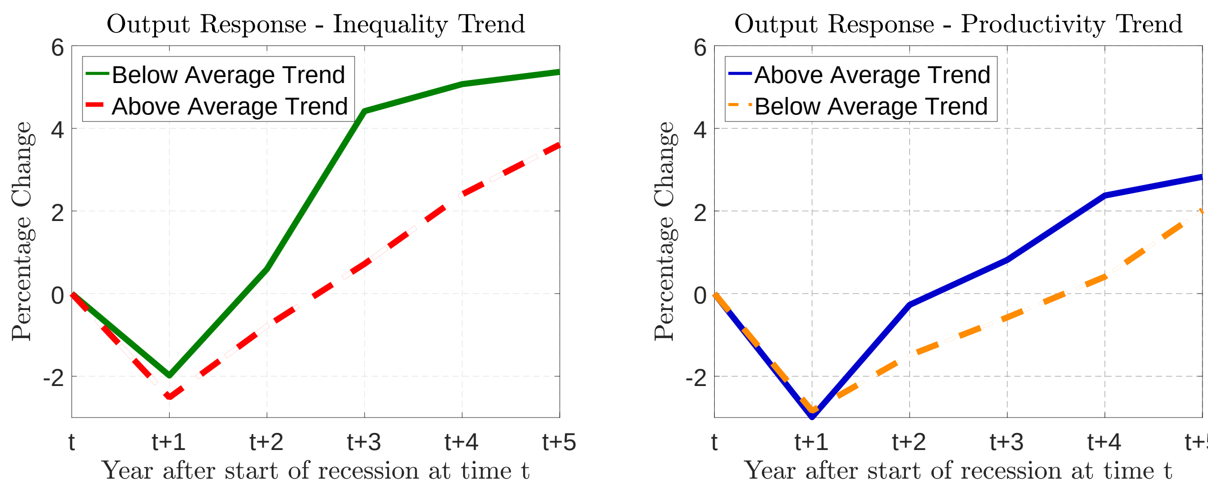


Figure 7: ***Behavior of Output during Recessions.*** *Average percentage change in real GDP after the start of a recession at time t, differentiated by pre-recession changes in the top 1% income share and labor productivity (more than one standard deviation above or below average growth over the three preceding years).*

If recessions are preceded by changes in top income inequality substantially above average, then output declines more strongly compared with recessions that are characterized by changes in top income inequality much below average. Similarly, output also falls more strongly during recessions that are preceded by unusually low productivity growth, compared with the ones associated with substantially 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 significance of the various estimates. To this end, I use the local projection approach by Jordà (2005).

5.1 Local Projections

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

$$y_{k,t+h} - y_{k,t} = \beta^h + \gamma^h \Delta_3 Z_{k,t} + \Gamma_1^h X_{k,t} + \Gamma_2^h X_{k,t-1} + u_{k,t}^h \quad \text{for } h = 1, \ldots, 5 \ , \tag{2}$$

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.[31]

The set of regressions are estimated only for periods t that indicate the start of a recession as defined in Section 2.1. The coefficient β^h therefore gives the average percentage change in output h years after the start of a recession. The additional effect of the buildup period on the response of output is captured by $\Delta_3 Z_{k,t}$.[32] The variable $\Delta_3 Z_{k,t}$ follows the definition in Section 3 and is again normalized to mean zero and standard deviation one. The typical percentage change of output after the start of a recession that was also preceded by a one-standard-deviation change in Z above its mean over the previous three years is then given by $\beta^h + \gamma^h$ at horizon h.

Due to the differences in the availability of data, I again obtain evidence for top income inequality and productivity separately. In particular, I consider changes in the top 1% income share and labor productivity growth which take the place of variable Z in (2). The estimation results are given in Tables 7 and 8. Figure 8 summarizes the findings graphically. 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.

[31] 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.

[32] Here, I choose three-year differences to avoid an overlap with previous business cycle peaks. However, I find that the following results are robust to considering four- or five-year windows for the change in Z.

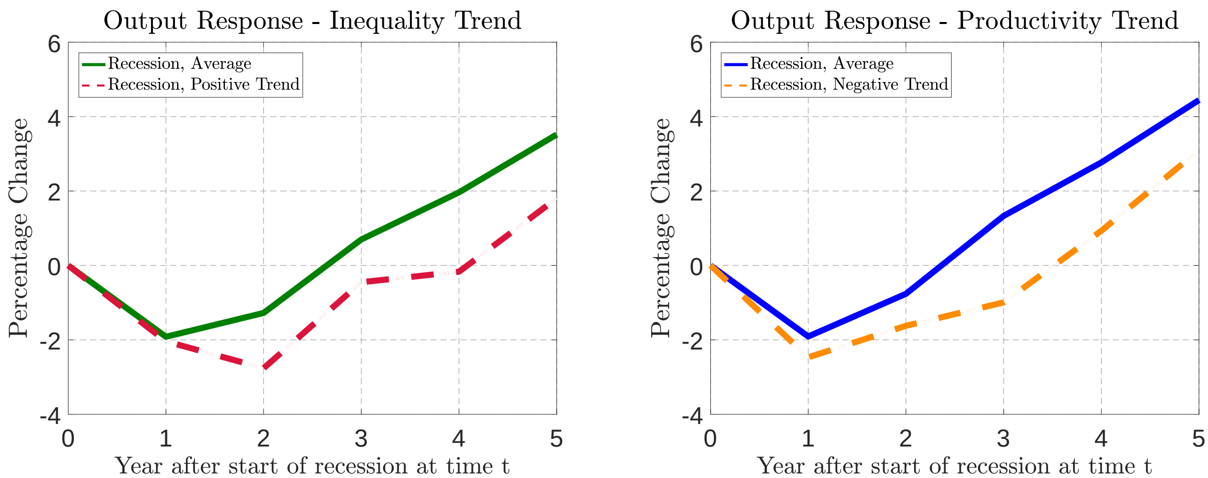


Figure 8: ***Behavior of Output during Recessions.*** *Estimated percentage change in real GDP after start of a recession at time t, differentiated by pre-recession trends in top income inequality and productivity (1.5 standard deviation above or below mean).*

Recessions that occur after excess increases in top income inequality or low productivity growth are associated with stronger declines in output. Tables 7 and 8 show that these differences $-$ given by the coefficients $\hat{\gamma}^h$ $-$ are 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.

Year: h		1	2	3	4	5
Average Recession	$\hat{\beta}^h$	-1.917***	-1.277***	0.698	1.964***	3.518***
		(0.208)	(0.360)	(0.577)	(0.688)	(0.722)
Δ_3Income Share 1%$_t$	$\hat{\gamma}^h$	-0.081	-0.991**	-0.766	-1.422*	-1.144
		(0.226)	(0.391)	(0.627)	(0.747)	(0.784)
Observations		98	98	98	98	98

Table 7: ***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
Average Recession	$\hat{\beta}^h$	-1.909***	-0.763***	1.331***	2.767***	4.446***
		(0.149)	(0.283)	(0.391)	(0.509)	(0.569)
$\Delta_3\log(\mathrm{LP})_\mathrm{t}$	$\hat{\gamma}^h$	0.374*	0.573	1.550***	1.224*	0.898
		(0.204)	(0.388)	(0.537)	(0.699)	(0.780)
Observations		177	177	177	177	177

Table 8: ***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,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Financial vs. Nonfinancial Recessions. For the regressions in (2), I treated all recessions equally. Next, I distinguish between recessions that are associated with financial crises ("financial recessions") and recessions that are not ("nonfinancial recessions") as in Jordà et al. (2013). Consider the set of regressions

$$\begin{aligned} y_{k,t+h} - y_{k,t} = \; & \Gamma_1^h X_{k,t} + \Gamma_2^h X_{k,t-1} + \beta_F^h F_{k,t} + \beta_N^h N_{k,t} \\ & + \gamma_F^h F_{k,t} \cdot \Delta_3 Z_{k,t} + \gamma_N^h N_{k,t} \cdot \Delta_3 Z_{k,t} + u_{k,t}^h \quad \text{for } h = 1, \ldots, 5 \;, \end{aligned} \tag{3}$$

where $y_{k,t}$, $X_{k,t}$, and $\Delta_3 Z_{k,t}$ are defined as above. $F_{k,t}$ and $N_{k,t}$ are binary variables indicating the beginning of financial and nonfinancial recessions as defined in Section 2.1 and listed in Table 10 in Appendix A.1.1. 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 $F_{k,t} \cdot \Delta_3 Z_{k,t}$ and $N_{k,t} \cdot \Delta_3 Z_{k,t}$. The estimated percentage change of output after the start of a financial recession that was also preceded by a one-standard-deviation change in Z above its mean during the previous three years is then given by $\beta_F^h + \gamma_F^h$ at horizon h; similarly, $\beta_N^h + \gamma_N^h$ for nonfinancial recessions.

The estimation results are shown in Tables 35 and 36 in Appendix A.4. First, the estimates confirm a well-known finding. Financial recessions are typically more severe than nonfinancial recessions, and these differences are by and large statistically significant. Second, the results with respect to the pre-recession trends in income inequality and productivity are similar to the ones above. However, there are only few observations left for financial recessions, which reduces the statistical significance for a range of estimates.

6 Conclusion

Rising top income inequality and low productivity growth are robust predictors of financial crises, and these relations are explained by their slow-moving trend components. Moreover, if recessions are preceded by such developments, then output declines more strongly subsequently. These are the findings based on a long-run historical data set of macrofinancial, productivity, and income inequality data for the vast majority of advanced economies. For the purpose of this paper, I have collected data on top income shares that exclude capital gains and thereby movements in asset prices. I hope that this data will be of use to other researchers in the future.

It is important to highlight that all my results represent predictive and not causal relations. Hence, it is a challenging but exciting task for future research to address the issue of causality. Nonetheless, my findings suggest that "real-economy factors" − productivity growth and the distribution of income − are relevant determinants for macrofinancial stability, and a buildup of risk occurs at a lower frequency than at conventional business cycles. The previous literature has highlighted a second set of "financial factors" − credit and asset price booms and a worsening of the current account − that are also strong early-warning indicators of financial crises. For these financial factors, I show that their predictive power arises from cyclical changes. The data therefore speak towards the traditional views by Kindleberger (1978) and Minsky (1986) that financial crises are preceded by temporary excesses in credit creation and asset prices. However, I also show that it is challenging to distinguish between trend and cycle in real time, another relevant issue to be addressed by future research.

Last, my findings have important implications for macrofinancial modeling. Theoretical models of financial crises should be able to match the described patterns in the data. While a few recent papers have attempted to replicate the fact that financial crises occur out of temporary credit-intensive booms (e.g., Paul, 2018), none of the current generation of macrofinance models allow for slow-moving trend changes to affect financial stability. This is another important area for future research, since data-consistent models are needed to analyze the effectiveness of various macroprudential policies.

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A Appendix

A.1 Data Description

Tables 9 and 10 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 9: ***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 10: ***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 2.2, 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

$$u_t = \left(\frac{\frac{Y_t}{K_t}}{\frac{Y}{K}_{|ss}}\right)^{\frac{\delta}{\delta+r}} ,$$

$$e_t = \left(\alpha \frac{Y_t}{C_t}\right)^{\frac{1}{1+\psi}} \quad ,$$

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

$$\alpha = 1 - \frac{K}{Y}_{|ss} (r + \delta) \quad ,$$

$$\psi = \frac{\alpha}{LS_{|ss}} - 1 \quad ,$$

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.

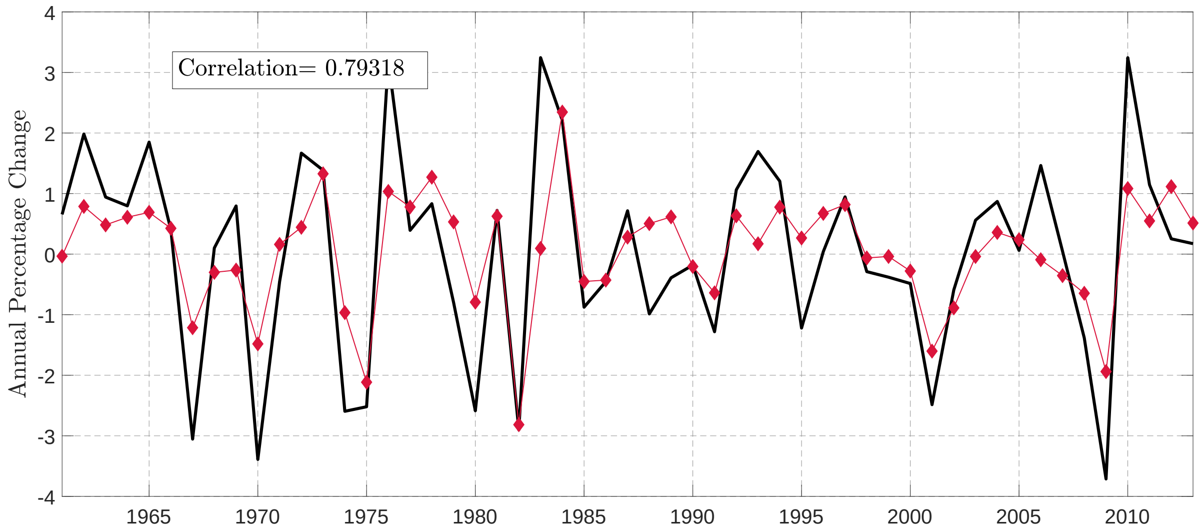

Figure 9: ***Comparison of utilization adjustment for the U.S.*** *Solid black series denotes the utilization adjustment by Fernald (2014) and red series with diamond markers denotes the utilization adjustment based on the approach by Imbs (1999).*

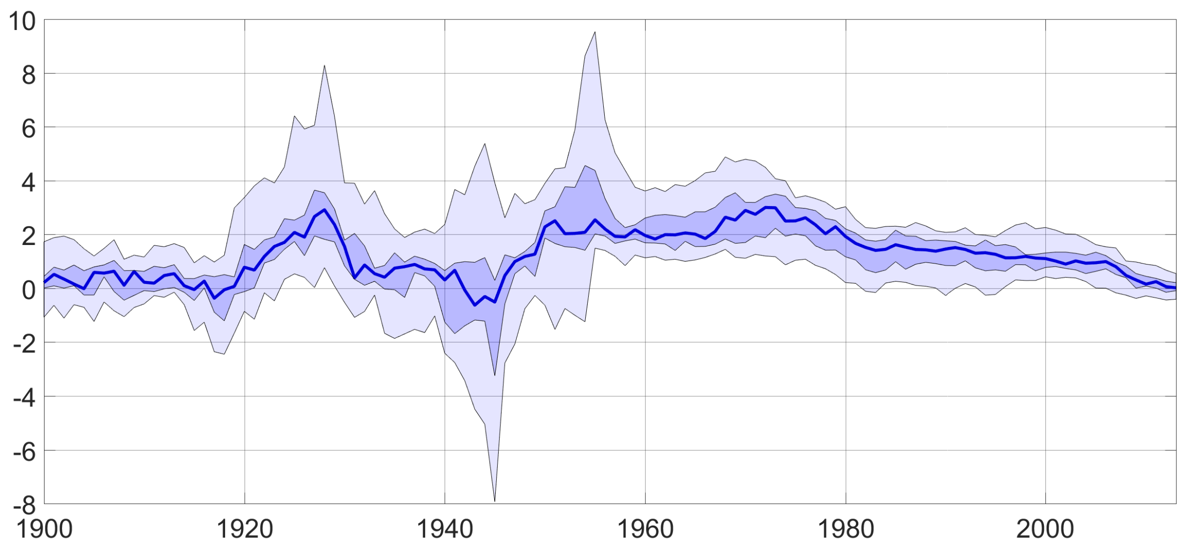

Figure 10: ***Ten-Year Moving Average of Util.-adj. TFP Growth.*** *Median,* 33^{rd}*,* 66^{th}*,* 90^{th}*, and* 10^{th} *percentiles shown.*

A.2 Predicting Financial Crises – Additional Evidence

A.2.1 Income Inequality

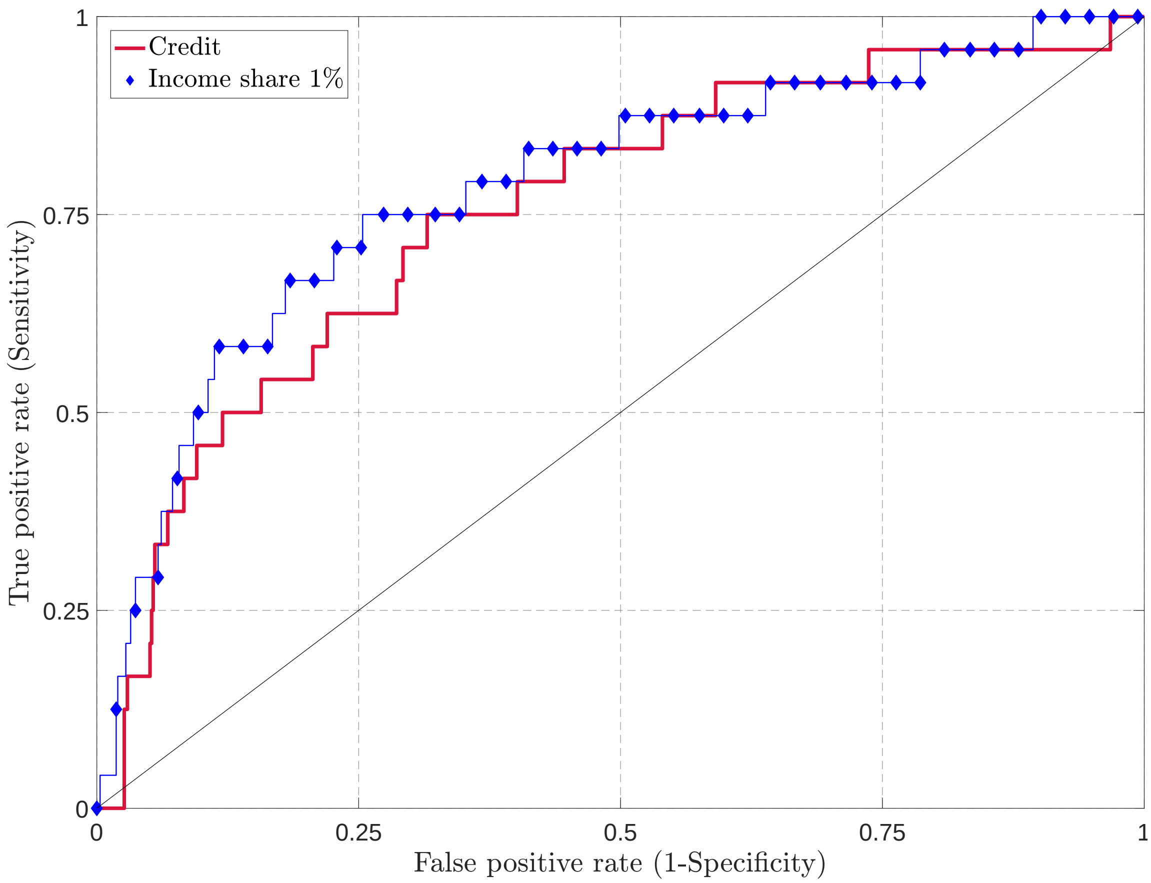

Figure 11: ***ROC Comparison.*** *Comparison of receiver operating characteristic curve for logistic probability models in columns 1 and 2 in Table 1. The area under the ROC is 0.764 for the model in column 1 (credit) and 0.777 for the model in column 2 (top 1% income share).*

	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)
$\Delta_4\log(\text{Credit})_{t-1}$	0.529***	0.438***	0.018***	0.435*	0.712**	0.429*	0.569***	0.020	0.513***
	(0.191)	(0.123)	(0.006)	(0.257)	(0.322)	(0.245)	(0.182)	(0.108)	(0.184)
	[0.013]	[0.011]		[0.025]	[0.011]	[0.010]	[0.014]	[0.001]	[0.012]
$\Delta_4\text{Income Share 1\%}_{t-1}$	0.663***	0.628***	0.019***	0.476	0.851***	0.452**	0.725***	-0.216*	
	(0.181)	(0.152)	(0.006)	(0.306)	(0.295)	(0.188)	(0.194)	(0.129)	
	[0.016]	[0.015]		[0.028]	[0.013]	[0.010]	[0.018]	[-0.013]	
$\Delta_4\log(\text{Income Share 1\%})_{t-1}$									0.700***
									(0.190)
									[0.016]
Number of crises / recessions	31	31	31	10	21	17	33	68	31
Observations	846	937	937	135	681	536	846	918	846
Countries	15	17	17	7	15	10	15	16	15
Country FE	✓		✓	✓	✓	✓	✓	✓	✓
p-value	0.945		0.024	0.996	0.938	0.834	0.916	0.510	0.883
Pseudo R^2	0.105	0.074	0.035	0.058	0.151	0.080	0.115	0.035	0.110
AUROC	0.791***	0.769***	0.806***	0.722***	0.815***	0.754***	0.811***	0.645***	0.792***
	(0.041)	(0.035)	(0.036)	(0.079)	(0.054)	(0.057)	(0.034)	(0.034)	(0.038)

Table 11: ***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)	(6)
$\Delta_3\log(\text{Credit})_{t-1}$	0.936**			1.036**	0.979**	1.044**
	(0.406)			(0.471)	(0.477)	(0.477)
	[0.020]			[0.016]	[0.016]	[0.016]
Δ_3Income Share $1\%_{t-1}$		0.832***		0.861***		0.908***
		(0.200)		(0.200)		(0.280)
		[0.020]		[0.013]		[0.014]
Δ_3Income Share $10\%_{t-1}$			0.741***		0.831***	-0.068
			(0.172)		(0.231)	(0.299)
			[0.019]		[0.013]	[-0.001]
Number of crises	26	26	26	26	26	26
Observations	698	698	698	698	698	698
Countries	14	14	14	14	14	14
Country FE	✓	✓	✓	✓	✓	✓
p-value	0.289	0.038	0.025	0.010	0.078	0.020
Pseudo R^2	0.103	0.098	0.076	0.171	0.146	0.171
AUROC	0.777***	0.760***	0.726***	0.840***	0.826***	0.840***
	(0.049)	(0.051)	(0.047)	(0.045)	(0.043)	(0.045)

Table 12: ***Predicting Financial Crises − Three-Year Differences.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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)
$\Delta_5\log(\text{Credit})_{t-1}$	0.915**			0.995**	0.919**	1.087**
	(0.439)			(0.439)	(0.434)	(0.476)
	[0.022]			[0.017]	[0.019]	[0.017]
Δ_5Income Share 1%$_{t-1}$		0.810***		0.882***		1.382***
		(0.210)		(0.217)		(0.325)
		[0.021]		[0.015]		[0.022]
Δ_5Income Share 10%$_{t-1}$			0.514**		0.567*	-0.668**
			(0.255)		(0.332)	(0.338)
			[0.015]		[0.012]	[-0.010]
Number of crises	26	26	26	26	26	26
Observations	656	656	656	656	656	656
Countries	14	14	14	14	14	14
Country FE	✓	✓	✓	✓	✓	✓
p-value	0.450	0.055	0.478	0.018	0.153	0.000
Pseudo R^2	0.099	0.098	0.062	0.160	0.120	0.169
AUROC	0.771***	0.748***	0.711***	0.820***	0.801***	0.828***
	(0.050)	(0.052)	(0.054)	(0.047)	(0.047)	(0.047)

Table 13: ***Predicting Financial Crises – Five-Year Differences.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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)
$\Delta_4\log(\text{Credit})_{t-1}$	0.458*			0.510*	0.420*
	(0.260)			(0.276)	(0.254)
	[0.013]			[0.011]	[0.011]
Δ_4Income Share $1\%_{t-1}$		0.721***		0.749***	
		(0.217)		(0.228)	
		[0.018]		[0.016]	
Δ_4Income Share $10\%_{t-1}$			0.492**		0.476**
			(0.217)		(0.229)
			[0.013]		[0.012]
Number of crises	27	27	27	27	27
Observations	726	726	726	726	726
Countries	15	15	15	15	15
Country FE	✓	✓	✓	✓	✓
p-value	0.584	0.845	0.765	0.803	0.739
Pseudo R^2	0.067	0.101	0.071	0.122	0.088
AUROC	0.713***	0.758***	0.724***	0.777***	0.754***
	(0.051)	(0.051)	(0.054)	(0.051)	(0.052)

Table 14: ***Predicting Financial Crises − Financial Crises Dates by Reinhart and Rogoff (2009b).*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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)
$\Delta_4\log(\text{Credit})_{t-1}$	0.998**			1.001**	0.958**
	(0.397)			(0.417)	(0.458)
	[0.023]			[0.018]	[0.018]
Δ_4Income Share $1\%_{t-1}$		0.763**		0.721**	
		(0.317)		(0.313)	
		[0.019]		[0.013]	
Δ_4Income Share $10\%_{t-1}$			0.739**		0.678**
			(0.298)		(0.343)
			[0.020]		[0.013]
Number of crises	15	15	15	15	15
Observations	417	417	417	417	417
Countries	13	13	13	13	13
Country FE	✓	✓	✓	✓	✓
p-value	0.768	0.998	0.996	0.891	0.917
Pseudo R^2	0.092	0.086	0.061	0.150	0.121
AUROC	0.735***	0.756***	0.703***	0.805***	0.771***
	(0.075)	(0.071)	(0.073)	(0.071)	(0.075)

Table 15: ***Predicting Financial Crises – Financial Crises Dates by Laeven and Valencia (2013).*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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)
$\Delta_4 \log(\text{Credit})_{t-1}$	0.403			0.401	0.396
	(0.345)			(0.357)	(0.346)
	[0.010]			[0.010]	[0.010]
Δ_4Income Share $1\%_{t-1}$		0.447*		0.442*	
		(0.246)		(0.238)	
		[0.011]		[0.011]	
Δ_4Income Share $10\%_{t-1}$			0.094		0.049
			(0.260)		(0.263)
			[0.003]		[0.001]
Number of crises	14	14	14	14	14
Observations	479	479	479	479	479
Countries	11	11	11	11	11
Country FE	✓	✓	✓	✓	✓
p-value	0.998	1.000	1.000	0.999	0.998
Pseudo R^2	0.023	0.028	0.009	0.042	0.023
AUROC	0.635	0.656**	0.564	0.671**	0.636
	(0.085)	(0.064)	(0.077)	(0.081)	(0.085)

Table 16: ***Predicting Financial Crises − Financial Crises Dates by Bordo et al. (2001).*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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)
$\Delta_4\log(\text{Credit})_{t-1}$	0.493**			0.515**	0.477*
	(0.244)			(0.248)	(0.252)
	[0.019]			[0.019]	[0.017]
Δ_4Income Share $1\%_{t-1}$		0.385*		0.388*	
		(0.211)		(0.202)	
		[0.015]		[0.014]	
Δ_4Income Share $10\%_{t-1}$			0.471**		0.450**
			(0.189)		(0.183)
			[0.018]		[0.016]
Number of crises	28	28	28	28	28
Observations	553	553	553	553	553
Countries	16	16	16	16	16
Country FE	✓	✓	✓	✓	✓
p-value	0.263	0.904	0.872	0.447	0.484
Pseudo R^2	0.066	0.065	0.066	0.086	0.084
AUROC	0.698***	0.712***	0.708***	0.737***	0.733***
	(0.047)	(0.052)	(0.051)	(0.046)	(0.047)

Table 17: ***Predicting Financial Crises* $-$ *Financial Distress Measure by Romer and Romer (2017a).*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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)
$\Delta_4 \log(\text{Credit})_{t-1}$	0.890**	0.757**	0.866**	0.741**	0.932***	0.731**
	(0.375)	(0.354)	(0.377)	(0.350)	(0.322)	(0.305)
	[0.015]	[0.016]	[0.014]	[0.016]	[0.014]	[0.015]
Δ_4Income Share $1\%_{t-1}$	0.880***		0.851***		0.869***	
	(0.267)		(0.240)		(0.244)	
	[0.014]		[0.014]		[0.013]	
Δ_4Income Share $10\%_{t-1}$		0.563**		0.564**		0.494**
		(0.286)		(0.243)		(0.218)
		[0.012]		[0.012]		[0.010]
Number of crises	27	27	27	27	28	28
Observations	734	734	785	785	818	818
Countries	14	14	14	14	14	14
Country FE	✓	✓	✓	✓	✓	✓
p-value	0.728	0.856	0.932	0.964	0.842	0.948
Pseudo R^2	0.159	0.115	0.144	0.101	0.164	0.115
AUROC	0.825***	0.808***	0.820***	0.789***	0.826***	0.789***
	(0.045)	(0.043)	(0.045)	(0.043)	(0.043)	(0.044)

Table 18: ***Predicting Financial Crises - Linear Interpolation.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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%$_{t-1}$	0.669***	0.637***	0.649***	0.764***	0.764***	0.764***	0.662***	0.679***
	(0.172)	(0.169)	(0.171)	(0.189)	(0.207)	(0.189)	(0.173)	(0.166)
	[0.018]	[0.017]	[0.017]	[0.019]	[0.020]	[0.019]	[0.018]	[0.018]
Number of crises	31	30	31	31	31	31	31	31
Observations	858	834	858	845	858	845	858	843
Countries	15	15	15	15	15	15	15	15
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
p-value	0.990	0.993	0.997	0.980	0.983	0.980	0.989	0.977
Pseudo R^2	0.068	0.069	0.073	0.096	0.077	0.095	0.068	0.081
AUROC	0.722***	0.721***	0.729***	0.736***	0.729***	0.735***	0.722***	0.739***
	(0.045)	(0.047)	(0.044)	(0.054)	(0.052)	(0.054)	(0.045)	(0.048)

Table 19: ***Predicting Financial Crises.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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%$_{t-1}$	0.664***	0.707***	0.785***	0.630***	0.746***	0.715***	0.551***
	(0.201)	(0.173)	(0.268)	(0.175)	(0.176)	(0.208)	(0.186)
	[0.012]	[0.013]	[0.010]	[0.015]	[0.016]	[0.017]	[0.012]
Number of crises	31	30	21	31	31	30	30
Observations	843	824	613	854	853	825	845
Countries	15	15	15	15	15	15	15
Country FE	✓	✓	✓	✓	✓	✓	✓
p-value	0.629	0.831	0.430	0.982	0.956	0.970	0.962
Pseudo R^2	0.161	0.137	0.188	0.100	0.109	0.103	0.100
AUROC	0.819***	0.819***	0.843***	0.770***	0.792***	0.767***	0.768***
	(0.033)	(0.034)	(0.043)	(0.045)	(0.035)	(0.047)	(0.039)

Table 20: ***Predicting Financial Crises.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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 $-$ to $-$ 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 21: ***Predicting Financial Crises.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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

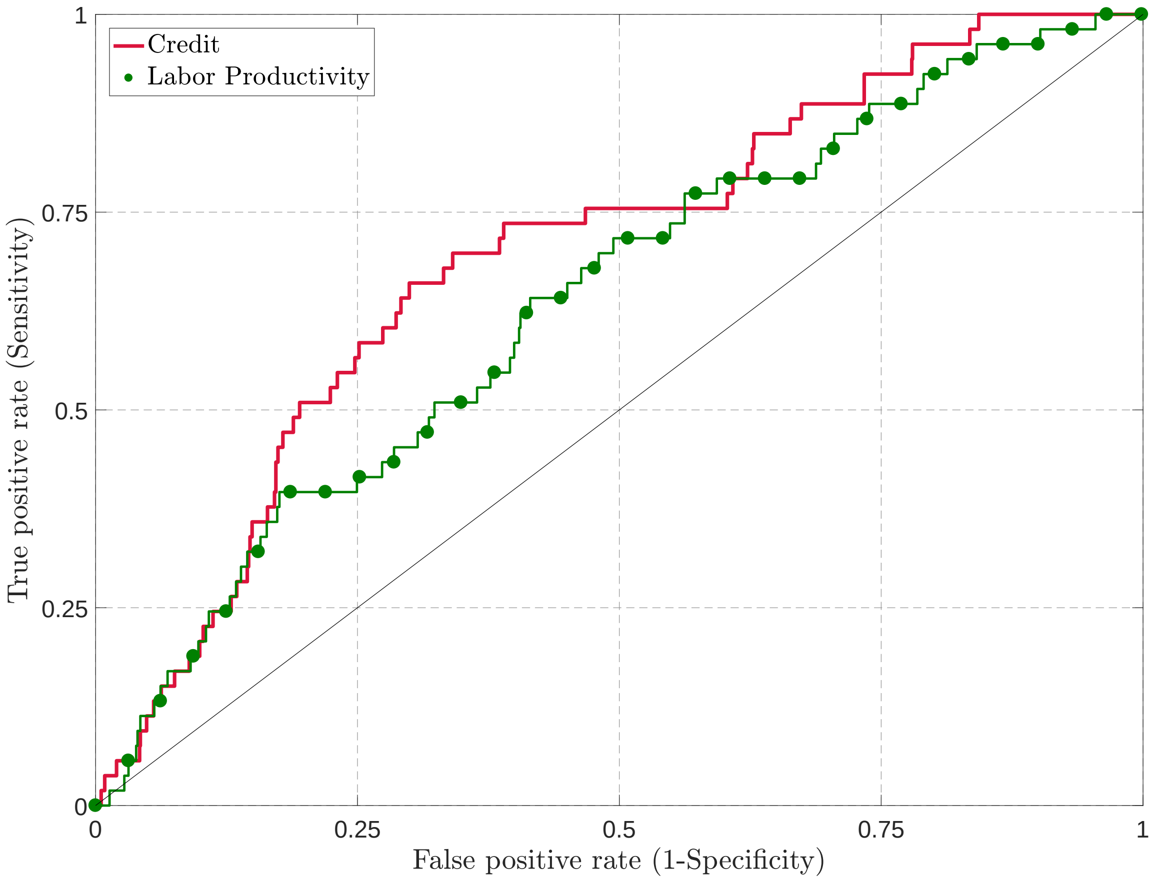

Figure 12: ***ROC Comparison.*** *Comparison of receiver operating characteristic curve for logistic probability models in columns 1 and 3 in Table 3. The area under the ROC is 0.695 for the model in column 1 (credit) and 0.636 for the model in column 3 (labor productivity).*

	(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]
$\Delta_4\log(\text{TFP})_{t-1}^{\text{util.}-\text{adj.}}$			-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 22: ***Predicting Financial Crises − Post-WWII.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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
$\Delta_4\log(\text{Credit})_{t-1}$	0.364***	0.339***	0.020***	0.334***	0.700***	0.259**	0.326***	0.082	0.433***
	(0.105)	(0.091)	(0.005)	(0.127)	(0.205)	(0.104)	(0.110)	(0.082)	(0.134)
	[0.011]	[0.011]		[0.016]	[0.011]	[0.006]	[0.009]	[0.007]	[0.012]
$\Delta_4\log(\text{LP})_{t-1}$	-0.352***	-0.290***	-0.014***	0.249	-1.003***	-0.468***	-0.283***	-0.119	
	(0.101)	(0.083)	(0.004)	(0.151)	(0.252)	(0.118)	(0.096)	(0.092)	
	[-0.010]	[-0.009]		[0.012]	[-0.015]	[-0.011]	[-0.008]	[-0.010]	
$\Delta_4\log(\text{Input Factors})_{t-1}$									0.103
									(0.145)
									[0.003]
Number of crises / recessuib	63	63	63	39	24	38	60	172	53
Observations	1734	1734	1734	666	974	1327	1734	1734	1552
Countries	17	17	17	16	16	15	17	17	17
Country FE	✓		✓	✓	✓	✓	✓	✓	✓
p-value	0.890		0.321	0.910	0.998	0.977	0.959	0.465	0.963
Pseudo R^2	0.051	0.027	0.018	0.050	0.100	0.052	0.043	0.017	0.045
AUROC	0.705***	0.700***	0.727***	0.699***	0.766***	0.726***	0.692***	0.596***	0.695***
	(0.032)	(0.030)	(0.029)	(0.040)	(0.042)	(0.040)	(0.032)	(0.023)	(0.035)

Table 23: ***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)
$\Delta_3\log(\text{Credit})_{t-1}$	0.441**			0.504**	0.562**
	(0.190)			(0.222)	(0.226)
	[0.012]			[0.013]	[0.014]
$\Delta_3\log(\text{TFP})_{t-1}^{\text{util.}-\text{adj.}}$		-0.295**		-0.414***	
		(0.132)		(0.115)	
		[-0.008]		[-0.011]	
$\Delta_3\log(\text{LP})_{t-1}$			-0.338***		-0.525***
			(0.098)		(0.085)
			[-0.010]		[-0.013]
Number of crises	54	54	54	54	54
Observations	1602	1602	1602	1602	1602
Countries	17	17	17	17	17
Country FE	✓	✓	✓	✓	✓
p-value	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.046	0.027	0.029	0.061	0.070
AUROC	0.701***	0.630***	0.644***	0.720***	0.732***
	(0.035)	(0.039)	(0.036)	(0.036)	(0.033)

Table 24: ***Predicting Financial Crises −Three-Year Differences.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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)
$\Delta_5\log(\text{Credit})_{t-1}$	0.500***			0.586***	0.656***
	(0.175)			(0.195)	(0.205)
	[0.014]			[0.015]	[0.016]
$\Delta_5\log(\text{TFP})_{t-1}^{\text{util.}-\text{adj.}}$		-0.269**		-0.420***	
		(0.113)		(0.086)	
		[-0.008]		[-0.011]	
$\Delta_5\log(\text{LP})_{t-1}$			-0.325***		-0.557***
			(0.096)		(0.084)
			[-0.010]		[-0.014]
Number of crises	52	52	52	52	52
Observations	1501	1501	1501	1501	1501
Countries	17	17	17	17	17
Country FE	✓	✓	✓	✓	✓
p-value	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.049	0.023	0.026	0.064	0.075
AUROC	0.695***	0.624***	0.637***	0.717***	0.736***
	(0.037)	(0.039)	(0.037)	(0.034)	(0.031)

Table 25: ***Predicting Financial Crises − Five-Year Differences.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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 26: ***Predicting Financial Crises − Financial Crises Dates by Reinhart and Rogoff (2009b).*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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 27: ***Predicting Financial Crises − Financial Crises Dates by Laeven and Valencia (2013).*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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 28: ***Predicting Financial Crises − Financial Crises Dates by Bordo et al. (2001).*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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)
$\Delta_4\log(\text{Credit})_{t-1}$	0.226			0.399*	0.479**
	(0.195)			(0.205)	(0.207)
	[0.008]			[0.011]	[0.013]
$\Delta_4\log(\text{TFP})_{t-1}^{\text{util.-adj.}}$		-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)

Table 29: ***Predicting Financial Crises − Financial Distress Measure by Romer and Romer (2017a).*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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 30: ***Predicting Financial Crises.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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 31: ***Predicting Financial Crises.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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

$\Delta_4\log(\text{Credit})_{t-1}$	0.446***			0.438***	0.551***	0.523***
	(0.122)			(0.123)	(0.141)	(0.137)
	[0.013]			[0.011]	[0.015]	[0.012]
$\Delta_4\text{Income Share }1\%_{t-1}$		0.632***		0.628***		0.592***
		(0.145)		(0.152)		(0.151)
		[0.017]		[0.015]		[0.014]
$\Delta_4\log(\text{LP})_{t-1}$			-0.226*		-0.379***	-0.291**
			(0.131)		(0.128)	(0.123)
			[-0.007]		[-0.010]	[-0.007]
Number of crises	31	31	31	31	31	31
Observations	937	937	937	937	937	937
Countries	17	17	17	17	17	17
Country FE						
p-value						
Pseudo R^2	0.027	0.049	0.006	0.074	0.043	0.084
AUROC	0.674***	0.717***	0.586*	0.769***	0.709***	0.774***
	(0.047)	(0.042)	(0.049)	(0.035)	(0.042)	(0.034)

Table 32: ***Predicting Financial Crises.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. 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 Trend vs. Cycle − Additional Results

	Stock Prices		House Prices		Credit		Current Account	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_4(.)_{t-1}$	0.497***		0.803***		0.708***		-0.592***	
	(0.107)		(0.290)		(0.220)		(0.161)	
	[0.012]		[0.017]		[0.015]		[-0.013]	
Cycle		0.665***		1.158***		1.056***		-0.726***
		(0.150)		(0.429)		(0.317)		(0.193)
		[0.016]		[0.024]		[0.022]		[-0.016]
Trend		0.303*		0.945***		0.691***		-0.401**
		(0.170)		(0.363)		(0.249)		(0.196)
		[0.007]		[0.020]		[0.015]		[-0.009]
Number of crises	35	35	30	30	36	36	36	36
Observations	1140	1140	934	934	1171	1171	1195	1195
Countries	17	17	16	16	17	17	17	17
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
p-value	0.566	0.000	0.108	0.033	0.001	0.001	0.000	0.000
Pseudo R^2	0.044	0.044	0.083	0.085	0.069	0.072	0.055	0.055
AUROC	0.686***	0.688***	0.739***	0.746***	0.721***	0.726***	0.704***	0.704***
	(0.041)	(0.042)	(0.050)	(0.050)	(0.040)	(0.039)	(0.039)	(0.039)

Table 33: ***Predicting Financial Crises.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. Linear regression $y_t = \hat{\alpha} + \hat{\beta}_1 y_{t-5} + \hat{\beta}_2 y_{t-6} + \hat{\beta}_3 y_{t-7} + \hat{\beta}_4 y_{t-8}$ used to predict trend at time t following Hamilton (2018). 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, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.*

	Labor Productivity		Util.-adj. TFP		Top1% Share		Top1% Share Cap. Gains	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_4(.)_{t-1}$	-0.305***		-0.277***		0.735***		0.830***	
	(0.106)		(0.096)		(0.273)		(0.296)	
	[-0.008]		[-0.007]		[0.017]		[0.018]	
Cycle		-0.203*		-0.245**		0.994***		1.100***
		(0.107)		(0.097)		(0.361)		(0.396)
		[-0.005]		[-0.006]		[0.023]		[0.024]
Trend		-0.488**		-0.482**		0.774**		0.885**
		(0.206)		(0.225)		(0.348)		(0.429)
		[-0.012]		[-0.012]		[0.018]		[0.019]
Number of crises	37	37	36	36	20	20	20	20
Observations	1220	1220	1190	1190	552	552	553	553
Countries	17	17	17	17	15	15	15	15
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
p-value	0.000	0.000	0.000	0.000	0.027	0.048	0.030	0.045
Pseudo R^2	0.034	0.038	0.033	0.038	0.105	0.106	0.114	0.119
AUROC	0.664***	0.675***	0.659***	0.673***	0.750***	0.755***	0.765***	0.780***
	(0.043)	(0.044)	(0.044)	(0.045)	(0.058)	(0.057)	(0.054)	(0.051)

Table 34: ***Predicting Financial Crises.*** *Results from logit regressions with binary financial crisis indicator as dependent variable. Linear regression* $y_t = \hat{\alpha} + \hat{\beta}_1 y_{t-5} + \hat{\beta}_2 y_{t-6} + \hat{\beta}_3 y_{t-7} + \hat{\beta}_4 y_{t-8}$ *used to predict trend at time t following Hamilton (2018). 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.4 Severity of Recessions − Additional Results

Year: h		1	2	3	4	5
Financial Recession ($F_{k,t}$)	$\hat{\beta}_F^h$	-2.208***	-3.041***	-1.531	-0.013	1.373
		(0.428)	(0.726)	(1.174)	(1.422)	(1.485)
Nonfinancial Recession ($N_{k,t}$)	$\hat{\beta}_N^h$	-1.782***	-0.460	1.729**	2.878***	4.511***
		(0.270)	(0.459)	(0.742)	(0.899)	(0.939)
Δ_3Income Share 1%$_t$ x ($F_{k,t}$)	$\hat{\gamma}_F^h$	-0.302	-0.430	-0.252	-0.484	0.241
		(0.250)	(0.424)	(0.685)	(0.830)	(0.866)
Δ_3Income Share 1%$_t$ x ($N_{k,t}$)	$\hat{\gamma}_N^h$	0.112	-0.535	-0.255*	-0.956*	-0.933
		(0.226)	(0.383)	(0.619)	(0.750)	(0.783)
$H_0 : \hat{\beta}_N^h = \hat{\beta}_F^h$ (*p-value*)		0.439	0.007	0.033	0.116	0.102
Observations, Financial Recessions		31	31	31	31	31
Observations, Nonfinancial Recessions		67	67	67	67	67

Table 35: ***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 ($F_{k,t}$)	$\hat{\beta}_F^h$	-2.475***	-3.170***	-1.753**	-0.662	0.799
		(0.305)	(0.555)	(0.781)	(1.025)	(1.146)
Nonfinancial Recession ($N_{k,t}$)	$\hat{\beta}_N^h$	-1.687***	0.185	2.545***	4.117***	5.881***
		(0.180)	(0.328)	(0.462)	(0.605)	(0.677)
$\Delta_3$log(LP)$_t$ x ($F_{k,t}$)	$\hat{\gamma}_F^h$	0.355**	-0.033	0.436	-0.294	-0.620
		(0.169)	(0.307)	(0.432)	(0.567)	(0.634)
$\Delta_3$log(LP)$_t$ x ($N_{k,t}$)	$\hat{\gamma}_N^h$	0.051	0.207	0.953*	1.074*	0.865
		(0.191)	(0.348)	(0.490)	(0.642)	(0.718)
$H_0 : \hat{\beta}_N^h = \hat{\beta}_F^h$ (*p-value*)		0.036	0.000	0.000	0.000	0.000
Observations, Financial Recessions		50	50	50	50	50
Observations, Nonfinancial Recessions		127	127	127	127	127

Table 36: ***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,* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

B Data Appendix

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Australia.

Years	
	Top Income Shares with Capital Gains
1921-2013 with interruptions	WID-series based on Atkinson and Leigh (2007). The series includes capital gains.
	Top Income Shares without Capital Gains
1970-2010	Corrected series from Burkhauser et al. (2015) that excludes capital gains and imputation credits.
	Important Capital Income Tax Laws
Before 1972	Capital gains were not taxed.
1972-1985	Realized capital gains for assets held less than one year were taxed.
Since 1986	Most realized capital gains were taxed, regardless of how long the asset was held (but only applying to assets purchased after September 19, 1985). Owner-occupied housing continued to be tax-exempt.

Belgium.

Years	
	Top Income Shares without Capital Gains
1990-2013	Series based on Decoster et al. (2017). Capital income is almost completely missing, since most is taxed with a withholding tax at the source and therefore not declared in tax forms. In particular, the series do not include capital gains.

Canada.

Years	
	Top Income Shares with Capital Gains
1920-1981 with interruptions	WID-series based on Saez and Veall (2005), including capital gains since 1972.
1982-2013	Market Income (incl. Cap. Gains) series from Statistics Canada's Longitudinal Database.[33]
	Top Income Shares without Capital Gains
1920-1981	Series from Saez and Veall (2005) that excludes capital gains.[34]
1982-2013	Market Income series from Statistics Canada's Longitudinal Database.[35]
	Important Capital Income Tax Laws
Before 1972	Realized capital gains were tax-exempt and not reported on tax statements.
Since 1972	Capital gains have been taxable to varying degrees (see Saez and Veall (2005) for details).

[33] The database is available at https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1110005501.
[34] The series can be found at Emmanuel Saez's website.
[35] The database is available at https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1110005501.

Switzerland.

Years	
	Top Income Shares without Capital Gains
1933-2013 with interruptions	WID-series based on Dell (2005), updated by Foellmi and Martínez (2017), all series exclude capital gains.

Germany.

Years	
	Top Income Shares with Capital Gains
1871-2013 with interruptions	WID-series based on Bartels (2017) that include capital gains.
	Top Income Shares without Capital Gains
2001-2008	Series based on Bartels (2017) that exclude capital gains. Micro-data exists only for the years 2001-2008.
	Important Capital Income Tax Laws
2009	Withholding tax on capital gains introduced.

Denmark.

Years	
	Top Income Shares with Capital Gains
1870-2010 with interruptions	WID-series based on Atkinson and Søgaard (2016) that include capital gains but likely to be small (see page 268).
	Important Capital Income Tax Laws
1922-1960	Capital gains were only included if they were accrued on intent (see Atkinson and Søgaard, 2016, page 268).
Since 1960	The treatment and placement of capital gains in the tax system was changed a number of times, but the changes in general kept capital gains not related to a taxpayer's livelihood (see Atkinson and Søgaard, 2016, page 268).

Spain.

Years	
	Top Income Shares with Capital Gains
1948-2012 with interruptions	WID-series based on Alvaredo and Saez (2009) that includes capital gains.
	Top Income Shares without Capital Gains
1981-2012	Series that exclude capital gains based on Alvaredo and Saez (2009) and the update by Alvaredo and Bauluz (2014).
	Important Capital Income Tax Laws
Since 1979	Capital gains are included in the tax base (see Alvaredo and Saez (2009) for details).

Finland.

Years	
	Top Income Shares without Capital Gains
1920-2009 with interruptions	WID-series based on Jäentti et al. (2010) that excludes capital gains.
	Important Capital Income Tax Laws
Since 1989 Since 1993	Capital gains partly subject to taxation. Capital gains taxes at the same rate as other property income, imputed rents from owner occupied housing exempted.

France.

Years	
	Top Income Shares without Capital Gains
1900-2013 with interruptions	WID-series based on Garbinti et al. (2018) that excludes capital gains (DINA-series).
	Top Income Shares with Capital Gains
1900-2013 with interruptions	Series based on Garbinti et al. (2018). (see Online Appendix B)

United Kingdom.

Years	
	Top Income Shares without Capital Gains
1908-2013 with interruptions	WID-series based on Atkinson (2005) and update by Alvaredo et al. (2018) that excludes capital gains.
	Important Tax Laws
Up to 1989	The income tax data relate to the 'tax unit', which consists of a married couple, or of a single adult or of a single minor with income in his or her own right.
From 1990	The total income is always associated with the individual aged 15 years or older.

Italy.

Years	
	Top Income Shares with Capital Gains
1974-2009 with interruptions	WID-series based on Alvaredo and Pisano (2010) which excludes most realized capital gains.
	Important Capital Income Tax Laws
Before 1998	Realized capital gains went mostly untaxed and not reported (see Alvaredo and Pisano, 2010).
Since 1998	Capital gains from qualified equities have been included in tax statements to varying degrees (see Alvaredo and Pisano, 2010, for details). Tax tabulations do not offer separate information about capital gains, but only few included in series.

Japan.

Years	
	Top Income Shares with Capital Gains
1886-2010	WID-series based on Moriguchi and Saez (2008) which includes realized capital gains.
	Top Income Shares without Capital Gains
1886-2000	Series without capital gains from Moriguchi and Saez (2008) (only top1%).[36]
2001-2010	Update by Alvaredo et al. (2012).
	Important Capital Income Tax Laws
Since 1947	Realized capital gains taxed.

Netherlands.

Years	
	Top Income Shares without Capital Gains
1920-2012 with interruptions	WID-series based on Atkinson and Salverda (2005) that excludes capital gains.

[36]The series can be found at Emmanuel Saez's website.

Norway.

Years	
	Top Income Shares with Capital Gains
1875-2011	WID-series based on Aaberge and Atkinson (2010) that includes capital gains.
	Top Income Shares without Capital Gains
2000-2013	Series without capital gains are based on Alstadsæter et al. (2017).
	Important Capital Income Tax Laws
1992	Tax reform that included wide reductions of taxes on capital income, resulting in a spike of the top income share series around this time (Fjærli and Aaberge, 2000).
2006	In January 2006, Norway changed its shareholder income tax code. In anticipation of the reform, dividend payouts strongly increased before 2006, resulting in a spike in the top income share series (Alstadsæter et al., 2017).

Portugal.

Years	
	Top Income Shares with Capital Gains
1936-2005 with interruptions	WID-series from Alvaredo (2009) that excludes most capital gains.
	Important Capital Income Tax Laws
Before 1989	Capital gains were almost completely untaxed.
Since 1989	Interest income taxed at the source and not reported in personal tax forms. Capital gains from public bonds, most real estate, and stocks held more than 12 months exempted. Remaining capital gains on tax statements likely small, see Alvaredo (2009) for details.

Sweden.

Years	
	Top Income Shares with Capital Gains
1903-2013 with interruptions	WID-series based on Roine and Waldenström (2008) that includes capital gains.
	Top Income Shares without Capital Gains
1903-2013 with interruptions	Series without capital gains are taken from the website of Daniel Waldenstroem.[37]
	Important Capital Income Tax Laws
1991, 1994	Tax reforms that lead to peaks in income shares, in particular the one that includes capital gains.

United States.

Years	
	Top Income Shares without Capital Gains
1913-2013	WID-series based on Piketty et al. (2018) and Piketty and Saez (2003) that excludes capital gains (DINA-series).
	Top Income Shares with Capital Gains
1913-2013	Updated series from Piketty and Saez (2003).

[37] The associated excel spreadsheet can be downloaded at http://www.uueconomics.se/danielw/Data.htm.

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