Inequality, Credit, and Crises: The Role of Culture*

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February 14, 2019

This paper investigates whether two cultural characteristics, long-termism and risk aversion, moderate the effect of income inequality on household credit growth. For an international sample of 16 OECD countries for the years 1970 to 2016, we find that rising income inequality is associated with lower credit growth in societies that are more risk averse and long-term oriented. Similarly, in the U.S., states with more long-term oriented and risk averse populations rely less on credit-financed consumption to deal with rising income inequality. We show that these findings are robust across many different specifications and in a quasi-natural experiment setting. Since credit expansions heighten the probability of banking crises, these results contribute to explaining why some countries are more likely to experience banking crises than others.

JEL Classification: D31, D91, E21, E51, G01, R11

Keywords: Income inequality, Banking crisis, Household credit, Culture, Long-term orientation, Risk aversion

*We are grateful for the comments and insights of Constantine Yannelis, and participants at the 6th Paris Financial Management Conference and the Finance Center Muenster Seminar Series.

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1 Introduction

In the three decades preceding the 2007/08 global financial crisis, income inequality grew significantly in many developed economies (IMF, 2007; OECD, 2011; Atkinson et al., 2011). At the same time, household credit evolved from being just a small fraction of overall bank credit at the beginning of the 1990s to subsequently exceeding the volume of firm credit (Büyükkarabacak and Valev, 2010). Rajan (2010) links these two phenomena and proposes that income inequality played a central role in promoting household credit expansions and, consequently, in the emergence of the U.S. financial crisis. Kumhof et al. (2015) formally analyze these relations in a DSGE framework and show that income inequality endogenously causes credit expansions. While the empirical findings of Perugini et al. (2015) and Yamarik et al. (2016) support the theory of Kumhof et al. (2015), Bordo and Meissner (2012) do not find a significant relation between inequality and credit growth.

We analyze how the relation between inequality and household credit growth is moderated by cultural dissimilarities. We expect that as inequality increases, more long-term oriented and risk averse societies are less prone to increasing their debt levels. Long-term oriented societies have a lower incentive to stabilize their immediate consumption at the expense of future consumption. Highly risk averse societies take more precautions and, hence, do not need to rely on taking out a loan whenever income inequality rises to maintain their consumption level. Therefore, these societies take less advantage of an expansion in credit supply following an income inequality shock.

We test these hypotheses across different countries and on a U.S. state-level. The international dataset consists of 16 OECD countries, covering the years 1970–2016. Our long-term orientation proxy is the identically named fifth dimension of Hofstede et al. (2010)'s six cultural dimensions model. To measure risk aversion, we use a country's health care coverage rate, as it increases with the degree of risk aversion of a population (Finkelstein and McGarry, 2006; De Meza and Webb, 2001). The results of our analysis show that long-termism and risk aversion have a statistically significant negative impact on the relation between income inequality and household credit growth. The effects of long-termism and risk aversion are also economically relevant. In the least long-term oriented country, Australia, the increase in household credit in response to an increase in inequality is three times larger than in a country with an average level of long-term orientation. In very long-term oriented countries, such as Germany and Japan, households even decrease their credit as inequality rises. For risk aversion, we find that after an initial increase of one percentage point in income inequality, the increase in the household credit-to-GDP ratio is 1.404% higher in the least risk averse country compared to the most risk averse country. These results are robust to including the typical control variables of previous studies (Bordo and Meissner, 2012; Perugini et al., 2015) and using different proxies for long-term orientation and risk aversion. Our findings are also robust to accounting for creditor rights (Djankov et al., 2007), additional cultural dimensions (Hofstede et al., 2010), and differences in governance and institutional standards (Kaufmann et al., 2011).

We replicate our analysis for the U.S. state-level. This setting naturally mitigates the possibility that omitted cross-country differences affect our findings and provides the opportunity for a quasi-natural experiment. We use anti-nationalism as a measure for long-termism because it has been shown to correlate with a society's long-term orientation (Hofstede et al., 2010, p.253), and health care coverage to measure risk aversion. In panel regressions, we find that an increase in inequality is associated with a smaller increase in household credit in states with a more long-term oriented and a more risk averse population. To prevent potential endogeneity issues, we analyze in a quasi-natural experiment how the effect of an exogenous shock in income inequality on credit growth depends on a state's risk aversion. We identify a natural disaster, Hurricane Katrina in 2005, as an exogenous shock to income inequality. Hurricane Katrina led to an increase in income inequality in the most impacted states in 2005, which sequentially caused a surge in household credit. Among the states most affected by the hurricane, the increase in credit was least pronounced in the state with the highest degree of risk aversion.[1]

Our research relates to the empirical literature on (i) inequality and credit growth and (ii) determinants of financial crises. First, our results help explaining the mixed findings

[1] We cannot conduct this analysis for long-termism because the states affected by Hurricane Katrina did not substantially differ in the their long-term orientation.

of previous work on the relation between inequality and household credit. Yamarik et al. (2016) demonstrate that inequality is positively related to total credit and housing credit across U.S. states. Internationally, Bordo and Meissner (2012) do not find any evidence of a significant link between inequality and credit growth. They show that credit growth is primarily determined by business cycles and interest rates. In contrast, Perugini et al. (2015) find that income inequality has a positive impact on total credit. Figure 1 supports the existence of this ambivalent relationship for a selection of countries. While in the U.S. and in the U.K., the link between income inequality and credit is evidently positive, in Japan and in Finland, it is less obvious that there exists a relation between both variables. Our findings provide a compelling explanation for the incompatible graphs presented in Figure 1. Japan's society can be classified as being long-term oriented. Scandinavian countries, such as Finland, are considered to be extremely risk averse, due to their highly developed social protection systems. It is thus not surprising that there does not appear to be a strong relationship between inequality and credit growth in these two countries.

[Figure 1 about here.]

Second, our work is also related to the empirical work on the relation between (household) debt levels and the probability of a financial crisis. Kaminsky and Reinhart (1999) show that the growth in the domestic credit-to-GDP ratio is strongly associated with the occurrence of currency, banking, and twin crises in an international dataset of 20 countries between the 1970s and 1995. Schularick and Taylor (2012) use a longer time period (1870-2008) than Kaminsky and Reinhart (1999), but similarly find that aggregate bank loans are a statistically significant determinant of financial crises. Büyükkarabacak and Valev (2010) find that specifically household credit is a predictor for banking crises in an international dataset of 37 developed and developing countries between 1990 and 2006. Generally, the empirical evidence agrees on a positive relation between (household) debt and banking crisis, which we confirm for our sample. Given the positive relation between credit growth and banking crises, our study helps to understand why in some OECD countries rising income inequality does not coincide with the occurrence of a banking crisis. The resulting policy implications of our findings are that policy makers should become aware of the time preference and risk aversion of their citizens. In particular in countries with short-term oriented or less risk averse societies, governments might, for example, want to limit credit growth and promote higher savings rates for households.

The remainder of the paper is organized as follows. Section 2 reviews the literature on income inequality, credit, and the two cultural dimensions. Section 3 describes the international dataset and displays basic summary statistics. Section 4 presents the results on inequality, credit and the two cultural dimensions for the international sample. Section 5 provides findings based on U.S. state-level data including the quasi-natural experiment. Section 6 presents confirmatory evidence on the relationship between credit growth and banking crises. Section 7 concludes.

2 The Effect of Cultural Differences on Credit Growth

In his book, Rajan (2010) presents a link between income inequality and credit expansions in the U.S. at the beginning of the 21st century. He points out that rising income inequality leads to political pressure for redistribution. However, the necessary policies to offset these inequalities – the redistribution of income via taxes and social spending – are generally difficult to agree upon in the prevalent U.S. political environment. Instead, large bipartisan support is likely to generate for the deregulation of credit markets, the path of least resistance, to avoid losing low- and middle-income households as voters. Having grown accustom to a certain level of consumption, low- and middle-income households widely seize this politically driven opportunity to attain an otherwise unjustifiable line of credit. These developments led to the growth of subprime mortgages and resulted in a massive surge in housing prices in the mid-2000s. Eventually, the lending was deemed unsustainable and once housing prices reversed in 2007, the scene was set for the 2008 banking crisis.

With this argumentation in mind, Kumhof et al. (2015) provide a theoretical model to analyze the effect of inequality on household credit levels in a DSGE framework, irrespective of any political system. They show that shocks to the income distribution permanently increase the share of income of top earners. Subsequently, the rich use most parts of their additional income to increase their credit supply to poorer households. Unsurprisingly, low- and middle-income households take advantage of this opportunity to maintain their consumption level. Meanwhile, the growth in lending and the higher levels of debt increase the probability of a financial crisis.

Focusing exclusively on the U.S., Iacoviello (2008) points out that income inequality is the most significant determinant for the rise in household debt during the 1980s and 1990s. Kumhof et al. (2015) calibrate their model with aggregate U.S. data, which support their theory. These findings are confirmed by Yamarik et al. (2016), who employ U.S. state-level data for their empirical analysis. In contrast, when international datasets are used, the empirical results become mixed. Bordo and Meissner (2012) do not find any significant effect that income inequality leads to credit booms for their sample of 14 OECD countries between 1920 and 2008. In contrast to Bordo and Meissner (2012), Gu and Huang (2014) allow for heterogeneous coefficients in their regression model and identify a significant positive impact of inequality on credit growth in Anglo-Saxon countries (i.e. U.S., U.K. or Australia). Furthermore, Perugini et al. (2015) find a significant positive relationship between inequality and credit growth for their dataset of 18 OECD countries between 1968 and 2006. Typically, these contradictory findings are explained by different institutional and political backgrounds across different countries (Perugini et al., 2015; Yamarik et al., 2016).

We offer a new perspective to understand the effect of inequality on credit growth. In particular, we distinguish between the effects of long-term orientation and risk aversion in a society.

Long-Term Orientation

We hypothesize that the impact of income inequality on household credit is lower in long-term oriented society in comparison to societies with a lower future time preference. This effect can also be shown by Kumhof et al. (2015)'s model. Although Kumhof et al. (2015) do not explicitly discuss this effect, their DSGE framework can be used to demonstrate that a higher future preference of low- and middle income households leads to a smaller impact of rising income inequality on the steady-state level of debt, as we show analytically in Appendix A.1. After a shock to income inequality, top income earners extend their credit supply in Kumhof et al. (2015)'s model, but the poorer households have to take the opportunity to borrow against their future income to maintain their current consumption level. The incentive to shift their consumption (from the future into the present) is higher for households with a lower future preference.

In contrast to short-term oriented societies, people in long-term societies are less sensitive to social trends in consumption ("keeping up with the Joneses") (Hofstede et al., 2010, p.242). They evaluate immediate consumption lower and value future consumption higher. Intuitively, long-term oriented societies might take less advantage of relaxed credit constraints, caused by an increased supply of savings (Kumhof et al., 2015) or by deregulated credit markets (Rajan, 2010). Their incentive to increase their current consumption at the expense of future consumption is lower – even if there exist compelling opportunities – and consequently, credit growth reacts less sensitive to income inequality shocks in long-term than in short-term oriented societies.

Risk Aversion

As mentioned above, less fortunate households have to increase their credit demand after a negative income inequality shock in order to maintain their consumption level (Kumhof et al., 2015). However, we hypothesize that highly risk averse societies possess a lower credit demand following an income inequality shock.

The underlying intuition is that highly risk averse households prefer a stable consumption stream. They tend to invest more in long-term assets (Modigliani and Sutch, 1966; Wachter, 2003) and their demand for insurance is larger (Mossin, 1968; Schlesinger, 1981; Dionne and Eeckhoudt, 1985) as compared to less risk averse households. Thus, households with pronounced risk aversion preferences introduce more measures to protect themselves against future economic shocks, e.g. increasing income inequality. Subsequently, they do not need as much credit as societies with a lower risk aversion level to stabilize their consumption after a negative shock to the income distribution.

This idea is reflected in Rajan (2010, pp.192–201)'s 'security and safety-net' recommendations. He argues that governments should take precautionary measures, such as introducing a universal health care system or long-term saving plans for workers. Households that live in societies with those systems in place are well prepared to face future economic hardships and do not need to rely on taking out a loan whenever income inequality rises to smooth their consumption. Hence, the effect of income inequality on credit growth is smaller in highly risk averse societies in comparison to societies with a lower level of risk aversion.

3 International Data

Our international dataset encompasses 16 developed economies with varying observation periods depending on data availability. The countries considered are Australia, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States. The unbalanced dataset dates back to 1970, whereas the most recent observation is from 2016.

The dependent variable in the regressions is the annual total credit to households expressed as a percentage of GDP (Code F3.1) from the Bank for International Settlements. This new credit measure allows us to particularly analyze the change in the household debt structure without confounding effects coming from business lending. Previous studies were forced to ex post control for debt of businesses and other private organizations due to the unavailability of this newly publicized household credit data (see, e.g., Bordo and Meissner, 2012; Perugini et al., 2015).

Measures of Income Inequality and Culture

To measure income inequality, we follow Bordo and Meissner (2012), Perugini et al. (2015), and Kirschenmann et al. (2016) and use the share of pre-tax national income going to the top 1% earners from the World Inequality Database (formerly known as the World Top

Incomes Database).[2] In robustness tests, we use the top 10% income share. The World Inequality Database systematically takes national accounts, survey data, fiscal data, and wealth rankings into consideration to precisely track the evolution of income and wealth levels. According to Piketty (2007), it allows for robust cross-countries comparisons over extended periods. In contrast, alternative indicators, such as the Gini or Theil index, tend to be rather unreliable given that their calculation often fails to address potential data inconsistencies (Piketty, 2014). Nevertheless, Leigh (2007) shows that the share of national income going to the top 1% is highly correlated with alternative income inequality measures, e.g., the Gini index.

In order to measure long-term orientation, we rely on the National Culture - Hofstede Insights database. It reports time-invariant scores ranging from 0 to 100 for six cultural dimensions based on Hofstede et al. (2010, p.11). In their database, Hofstede et al. (2010) only disclose cross-sectional scores given that there is normally continuity in cultural values. Even though technological progress may have changed the way in which people interact and socialize nowadays, the underlying preferences and implicit values – to impress others or to simply make a living - remain remarkably consistent over time and across countries (Hofstede et al., 2010, p.20). Hofstede's Long Term Orientation (LTO) dimension describes how societies process their own past while simultaneously dealing with current and future challenges. A high LTO score indicates that the country's society is rather pragmatic. People show an ability to cope with changing conditions and exhibit a strong propensity to save and invest. In contrast, a low LTO score suggests that people are normative in their thinking. They value traditions and possess comparably small propensities to save and invest. The use of the Hofstede dimensions is widespread, especially in the more recent empirical finance settings (see, e.g., Chui et al., 2010; Lievenbrück and Schmid, 2014; Eun et al., 2015; Karolyi, 2016; Cheon and Lee, 2017).

Our risk aversion proxy is a measure of health care coverage, provided by the OECD database. It quantifies the percentage of the total population that has public or private

[2] We replaced missing values for our income inequality measure using linear interpolation.

health insurance.[3] The health care coverage rate is an appropriate proxy for risk aversion because the demand for health insurance increases with the degree of risk aversion. This has been empirically shown by Finkelstein and McGarry (2006) and theoretically demonstrated by De Meza and Webb (2001) and Jullien et al. (2007). Similarly, Friedman (1974) and Barsky et al. (1997) also use the demand for health insurance to estimate risk aversion.[4]

Control Variables

We obtain indicators for nominal GDP, real GDP per capita, consumer prices, nominal short-term interest rates, current account balances, and broad-money (M2) from the Jordà-Schularick-Taylor Macrohistory Database, compiled by Jordà et al. (2017). We then scale the current account and broad money regressors by nominal GDP and adjust the nominal short-term interest rate for inflation. Among the explanatory variables, we use real GDP per capita since it has been demonstrated to be a significant determinant of credit supply (Levine, 1997; Levine et al., 2003; Claessens et al., 2006). We include current account balances-to-GDP to control for foreign capital inflows. These capital inflows have been linked to significant credit expansions and stock market booms (see, e.g., Calvo et al., 1994; Mendoza and Terrones, 2008; Caballero, 2016). The two remaining variables, the real short-term interest rate and the broad money supply-to-GDP ratio, account for the prevalent monetary policy environment, especially given the increasing deployment of unconventional monetary policy measures. The database of Jordà et al. (2017) has been widely used in the existing empirical literature (see, e.g., Bordo and Meissner, 2012; Kirschenmann et al., 2016; Funke et al., 2016; Knoll et al., 2017).

[3] Due to the scarcity of observations for the U.S., we extrapolated its time series into the past. These newly created data points account for about 5% of all our health care coverage observations. In addition, we replaced missing values for Spain using linear interpolation.

[4] It appears reasonable to presume that we turn to the fourth dimension of the Hofstede Insights database to obtain our first risk aversion proxy, i.e. the Uncertainty Avoidance Index. However, according to Hofstede et al. (2010, pp.197-198), this dimension cannot be regarded in such a manner. Rather than being a measure of risk reduction, uncertainty avoidance aims at lowering ambiguity. People in such cultures prefer a clear structure in their everyday life with the implicit goal to avoid unpredictable events. Intriguingly, these people are often eager to participate in risky behavior, if their actions foster the reduction of uncertainties - such as starting a fight instead of waiting for the unknown to happen.

Unlike the previous studies that examined the relation between income inequality and household credit, we control for differences in creditor rights that we obtain from Djankov et al. (2007). They measure creditor protection by constructing a legal rights index of creditors similar to La Porta et al. (1997, 1998). This variable consists of four dimensions. A score of one is assigned when each of the following rights of secured lenders are defined in laws and regulations: (i) whether there exist restrictions, such as creditor consent, when a debtor files for reorganization; (ii) whether secure creditors are able to seize their collateral after the petition for reorganization is approved, that is, whether there is no automatic stay or asset freeze imposed by the court; (iii) whether secured creditors are paid first out of the proceeds of liquidating of bankrupt firm; and (iv) whether an administrator, and not management, is responsible for running the business during reorganization. The index is constructed from 1978 to 2003 and a rise in its value implies an increase in the quality of creditor protection.[5] As pointed out by Houston et al. (2010), stronger creditor protection tends to foster the risk taking behavior of banks – this might have consequences for household lending.

Summary Statistics

[Table 1 about here.]

Table 1 reports summary statistics on the variables used in the empirical model. The mean value of the credit variable implies that the average amount of loans extended to households accounts for 57.58% of GDP. This result is broadly similar to what Büyükkarabacak and Valev (2010) find in their dataset of 37 developed and developing countries between 1990 and 2006. The mean rate of the top 1% share measure indicates that, on average, 9.07% of the total national income is going to the top 1% earners. This value is slightly larger than those presented by Perugini et al. (2015) and Kirschenmann et al. (2016), since their datasets do not include the most recent decade. Regarding the LTO (Hofstede) variable, we see substantial variation across countries. The LTO scores range from 21 in Australia to 88 in Japan. As for the risk aversion dimension, proxied

[5] Due to the almost time-invariant nature of this index, we constantly extend it into the past and future based on the latest available observation.

by the health care coverage rate, it is not surprising that the average amount of people insured equals 97.50%, given that the majority of countries encompassed in our dataset set up universal health care systems at some point in time.

4 Credit Growth and Culture: Cross-Country Evidence

To quantify the extent to which cultural variations mediate the impact of income inequality on household credit growth, we use the following fixed effects model:

$$\begin{aligned}\Delta(Credit/GDP)_{i,t} = {} & \beta_1\Delta(Credit/GDP)_{i,t-1} + \beta_2\Delta(Credit/GDP)_{i,t-2} + \beta_3\Delta \textit{Top 1\% share}_{i,t-1} \\ & + \beta_4\Delta \textit{Top 1\% share}_{i,t-2} + \beta_5(Culture_i \times \Delta \textit{Top 1\% share}_{i,t-1}) \\ & + \beta_6(Culture_i \times \Delta \textit{Top 1\% share}_{i,t-2}) + \mathbf{X}' + z_i + u_t + e_{i,t} \ \ ,\end{aligned} \tag{1}$$

whereas subscripts i and t indicate countries and years, z_i and u_t are country- and year-specific effects, and $e_{i,t}$ resembles the error term. The inclusion of country- and year-specific effects represents a significant advantage of the panel data analysis, accounting for unobservable or inaccurately measured determinants of household credit, e.g. global liquidity conditions or institutional settings. In line with Bordo and Meissner (2012), Klein (2015), and Malinen (2016), all variables are stated in first differences (Δ) to remove the stochastic and deterministic trends they may possess – with the exception of the culture proxies and creditor rights. $Credit/GDP$ is our household credit-to-GDP ratio; *Top 1% share* is the share of national income going to the top 1%; and $\mathbf{X}'$ is the set of control variables described in Section 3. Following Bordo and Meissner (2012) and Perugini et al. (2015), we include the lagged dependent variable among the regressors. Most relevant to our analysis, Equation (1) includes two interaction terms, obtained by multiplying the lagged indicators of inequality with the different measures of cultural characteristics. These terms allow us to test whether more long-term oriented and risk averse societies rely less on credit-financed consumption in response to income inequality shocks.

[Table 2 about here.]

The estimation results of Equation (1) are shown in Table 2. In all five columns, we include the changes in income inequality over the previous two years. The estimates indicate that a change in the share of national income going to top 1% income earners has a significant effect on credit growth.

The central results for our LTO (Hofstede) proxy are presented in Columns (1) and (2). The coefficients on the interaction terms are significantly negative in all instances. They imply that the higher the level of long-term orientation, the less impact increasing income inequality has on household credit. For countries with an average level of Hofstede's LTO proxy, such as Spain or the United Kingdom, we estimate that in the second year following an initial increase of one percentage point in the share of national income going to the top 1% earners, the household credit-to-GDP ratio rises by about 0.11%.[6] In comparison, for Australia, which has the lowest LTO score in our sample, the estimates imply that in the second year following an increase of one percentage point in the top 1% income share, household credit increases by about 0.35% of GDP.[7] This effect is more than three times stronger than in an average LTO country. For countries with a very high LTO score of above 64.25 - such as France, the Netherlands, Switzerland, Germany, and Japan - it becomes evident that as income inequality increases, household credit as a share of GDP even decreases. For example, for Japan, which has the highest LTO score in our sample, in the second year after a one percentage point increase in income inequality, household credit-to-GDP declines by 0.19%. Thus, very long-term oriented societies reduce their credit-financed consumption as inequality increases by virtue of their pronounced concern for the future .

We obtain similar results for our risk aversion proxy, the health care coverage rate. The coefficients on both interaction terms in Columns (3) and (4) are significantly negative on the first lag. They indicate that the higher the degree of risk aversion, the smaller the effect of increasing income inequality on changes in household credit. One year after an initial increase of one percentage point in our income inequality measure, the increase in the household credit-to-GDP ratio is 1.404% higher in the country with the lowest health

[6]The average level of LTO, 50.438, is multiplied with the coefficient of the second interaction term, -0.008, in Column (2). This result is then added to the coefficient of the second lag of our income inequality proxy, 0.514.

[7]Australia's LTO score, 21, is multiplied with the coefficient of the second interaction term, -0.008, in Column (2). This result is then added to the coefficient of the second lag of our income inequality proxy, 0.514.

care coverage rate in comparison to a country with the highest health care coverage rate.[8] Again, we find that societies with the highest level of this culture proxy even decrease their credit as inequality increases.

The moderating effects of long-termism and risk aversion continue to stay significantly negative, even if both parameters are included in one regression, as demonstrated in Column (5).

Columns (2), (4), and (5) indicate that real GDP per capita growth is significantly positively associated with credit expansions. These results are in line with the findings of Bordo and Meissner (2012) and Perugini et al. (2015). Similar to Bordo and Meissner (2012), our results suggest that current account deficits have no significant relationship with household credit. The remaining estimates indicate that monetary policy has no significant impact on our dependent variable. Hence, households are more inclined to adjust their credit to the state of the overall economy and income inequality than to certain monetary policies. We find a positive and statistically significant effect of the interaction term between creditor rights and the top 1% income share in Columns (2) and (5). It suggests that the higher the standard of creditor rights, the greater the impact of increasing income inequality on household credit growth. This is in line with Djankov et al. (2007), who point out that countries with a higher quality of creditor protection tend to have higher levels of credit.

Taken together, highly risk averse and long-term oriented societies exhibit a lower increase in household credit caused by rising income inequality as compared to societies that have a lower degree of these attributes.

As a robustness test, we replace the top 1% income share by the top 10% income share. The findings remain similar and are reported in Table A1 in our appendix. Table A2 and Table A3 in our appendix also show that our results stay robust even if we include the real long-term interest rate or the natural logarithm of real GDP per capita or a second lag for each control variable in our baseline regression.

[8] The lowest health care coverage rate is 61 and the highest health care coverage rate is 100. To determine the effect of risk aversion, the coefficient of the first interaction term, -0.036, in Column (4) is multiplied with the difference between 61 and 100.

Alternative Long-Term Orientation and Risk Aversion Measures

To improve the robustness of our results, we construct alternative long-term orientation and risk aversion measures that are based on the fifth data collection wave (2005-2009) of the World Values Survey.[9]

As asserted by Hofstede et al. (2010, p.252), nations with higher percentages of their citizens being proud of their nationality tend to be short-term oriented. Thus, we create a new long-term orientation proxy called anti-nationalism. It measures the percentage of people, who do not answer the question "How proud are you to be [nationality]?" with the most extreme answer "very proud" on a 5-point Likert scale (Code V209).

We construct a new risk aversion proxy termed avoiding risk that looks at the percentage of people, who do not strongly identify with a person seeking adventures and taking risks by choosing the most extreme answer on a 6-point Likert scale (Code V86).

Table A4 in our appendix presents the estimation results with these alternative culture measures. Similar to our baseline results, all five regressions indicate that anti-nationalism and avoiding risk significantly moderate the impact of income inequality on household credit.

Additional Culture Variables

In addition to the sole analysis of long-term orientation and risk aversion preferences of societies, we also consider Hofstede's other culture dimensions to further scrutinize the validity of our baseline results. This implies the inclusion of five additional dimensions: (i) power distance index (PDI) which is concerned with the degree to which the less powerful members of a society accept and expect that power is distributed unequally; (ii) individualism versus collectivism (IDV) which highlights the preference for a loosely-knit social framework in which individuals are expected to take care of only themselves and their immediate families; (iii) masculinity versus femininity (MAS) which deals with the preference in society for achievement, heroism, assertiveness, and material rewards for success; (iv) indulgence versus restraint (IVR) which is concerned with as the extent to

[9] We have opted for the fifth data collection wave instead of the sixth (2010-2014) due to higher data availability.

which people try to control their desires and impulses, based on the way they were raised; and (v) uncertainty avoidance index (UAI) which deals with the degree to which the members of a society feel uncomfortable with uncertainty and ambiguity (Hofstede et al., 2010).

If time and risk preferences are truly significant determinants of what drives households to increase their leverage in the face of rising income inequality, then their coefficients should not be subsumed by the remaining Hofstede dimensions. The results presented in Table A5 in our appendix show that the only culture dimensions that stay significant in all three regressions are long-termism and risk aversion – thus, enhancing the legitimacy of our initial results. Interestingly, in Columns (1) and (3), the power distance and the uncertainty avoidance indices are significantly different from zero. The latter can be explained by the fact that members of society with high uncertainty avoidance are prone to being also more risk averse (Riddle, 1992). It is thus not surprising that in Columns (2) and (3), the negative coefficient on uncertainty avoidance decreases in size and significance due to the inclusion of our risk aversion proxy, the health care coverage rate. As for the positive and significant coefficient on power distance, it suggests that the higher the acceptance of an unequal income distribution, the less the demand for policies of redistribution (Alesina and La Ferrara, 2005). Instead, people are actively exploring alternative ways to improve their lives through taking advantage of relaxed credit constraints.

Institutional Environment

One potential point of concern is that culture might already be reflected in formalized governance settings. Hence, the question arises whether culture loses its impact on decision making when controlling for the governmental environment in a country. However, North (1990) shows that culture possesses a direct influence, which cannot be completely captured by formalizations. To ensure that this also holds true for our analysis, we repeat the baseline regression, but include six widely used governance indicators from the Worldwide Governance Indicators project published by the World

Bank (Kaufmann et al., 2011).

In particular, we control for: (i) political stability and absence of violence/terrorism (PVE); (ii) rule of law (RLE); (iii) voice and accountability (VAE); (iv) government effectiveness (GEE); (v) regulatory quality (RQE); and (vi) control of corruption (CCE). These aggregate indicators cover the period from 1996 to 2017. They reflect the views of a large number of business, citizen and expert survey respondents in developed and developing countries on the quality of governance in their respective countries. The results presented in Table A6 in our appendix indicate that our findings are not compromised by the inclusion of these indicators. Long-termism and risk aversion continue to have a significant moderating impact, which cannot be explained by the differences in governance settings.

5 Credit Growth and Culture: U.S. State-Level Evidence

We are aware of the potential drawback that our culture measures are highly correlated with the institutional settings of the different countries, which actually determine the level of household credit. Therefore, we controlled for creditor rights, country fixed effect, and multiple governance indicators in our previous regressions for the international dataset.

Nevertheless, we reexamine our results in a single country setting – the United States. The advantage of the U.S. is that its capital markets are predominantly regulated by federal laws (e.g. Consumer Credit Protection Act) and by federal agencies (e.g. United States Securities and Exchange Commission, SEC), while cultural difference continue to exist across states. These cultural disparities are a direct result of numerous waves of immigrants from various countries at different times, who brought their own culture to their new homes (Woodard, 2011, p.2). These waves of migration led to diverse ethnic compositions in each state.

We use annual data for the 50 U.S. states ranging from 2003 to 2015. Summary statistics and sources for each variable are presented in Table 3. Our dependent variable is the ratio of total household debt-to-state GDP. As in our international regression analysis, the inequality variables are the shares of income earned by the top 1% of the state population.

[Table 3 about here.]

To measure long-termism, we calculate a state-level anti-nationalism proxy by subtracting yearly non-prior service enlisted accessions to the U.S. military as a share of U.S. state population from 100. This proxy is based on the fact that nationalistic societies are more short-term oriented (Hofstede et al., 2010, p.253) and that militarism is highly correlated with nationalism (Eckhardt, 1969). The risk aversion proxy is the health care coverage rate for each state and year and is essentially equivalent to our risk aversion proxy on country level.

Our economic control measures are real GDP per capita and, similar to Yamarik et al. (2016), real wages per capita.

[Table 4 about here.]

Table 4 presents the estimates of the state-level analysis. The findings reinforce the results of our previous analysis and, thus, provide substantiating empirical evidence for our hypotheses. In detail, similar to Yamarik et al. (2016)'s state-level analysis, a rise in income inequality induces a significant positive effect on household credit. Furthermore, consistent with our international analysis, Columns (1) and (2) indicate that the effect of income inequality on household credit growth is lower in less nationalistic U.S. states. We are aware that the coefficients on our top income share variables in Columns (1) and (2) seem unusual, but they become plausible when the high average value of our anti-nationalism variable (99.488, Table 3) is taken into account. Due to this large average value of the anti-nationalism proxy, an increase of one percentage point in the top 1% income share leads to an expansion in the household credit-to-GDP ratio by only 0.04% in an average U.S. state in the second year after the impulse.[10] However, if we were to assume the lowest value of anti-nationalism, then our credit measure rises by about 0.81% in the second year following an increase of one percentage point in the top 1%

[10] The average value of our anti-nationalism proxy, 99.488, is multiplied with the coefficient of the second interaction term, -1.577, in Column (2). This result is then added to the coefficient of the second lag of our income inequality proxy, 156.937.

income share.[11] This effect is more than 20 times stronger than in an average U.S. state. Consequently, this result supports our hypothesis that the level of household credit in long-term orientated societies reacts less sensitive towards rising income inequality in comparison to short-term oriented societies.

Similarly, the estimates presented in Columns (3) and (4) allow for the conclusion that the impact of income inequality on household credit is lower in more risk averse U.S. states. As a robustness test, we replace the top 1% income share by the top 10% income share in Table A7 in our appendix. We obtain similar results.

It should be noted that due to the particular structure of our U.S. state-level sample - large N and small T - standard estimation methods for dynamic regression models are liable to lead to inconsistent parameter estimates (Nickell, 1981). This is due to the so-called dynamic panel bias, however this issue becomes insignificant, if T is sufficiently large. In this case, a standard fixed-effects estimator can be applied (Roodman, 2009a) – as was done for our international sample. Yet, for the U.S. state-level sample, we account for the dynamic panel bias as an additional robust check in Table A8 and Table A9 in our appendix. Similar to Perugini et al. (2015), we employ a (two-step) system GMM estimator. The system GMM estimator uses lagged values of endogenous regressors as instrumental variables. The validity of the moment conditions can be analyzed by use of the Hansen J-test of overidentified restrictions and by ensuring the absence of second-order serial correlation in the residuals. However, the employment of GMM estimators is prone to generate a large number of instruments, which in turn can weaken the Hansen J-test to such a degree where it reports implausibly good p-values of 1.000 (Andersen and Sørensen, 1996; Bowsher, 2002). We deal with this issue by collapsing instruments and limiting the number of lags used as instrumental variables.[12] The regression results presented in Table A8 and Table A9 in our appendix are comparable to those in Table 4 for the fixed effects estimation, albeit the size of the coefficients of interest are for most

[11] The lowest value of our anti-nationalism proxy, 99.005, is multiplied with the coefficient of the second interaction term, -1.577, in Column (2). This result is then added to the coefficient of the second lag of our income inequality proxy, 156.937.

[12] As a rule of thumb, Roodman (2009a) stresses the importance of restricting the amount of instrumental variables in such a manner that they do not exceed the number of individual units in the panel.

calibrations larger than in the fixed effects specification.

Quasi-Natural Experiment

We attempt to measure the moderating impact of cultural differences based on a quasi-natural experiment to rule out the possibility that our previous results are compromised by endogeneity problems induced by omitted variables that truly drive the variation in income inequality and hence in household credit.

We identify Hurricane Katrina, which was the costliest hurricane to strike the U.S. with \$108 billion in property damage, as an exogenous shock. The hurricane hit the American Gulf Coast at the end of August 2005 and damaged over 93,000 square miles of the United States.[13] Natural disasters usually have severe consequences for local economies. Tropical storms in particular do not only cause physical destruction and supply disruptions of resources but also strain households and lead to work interruptions (Shaughnessy et al., 2010).

Given that Alabama, Florida, Louisiana, and Mississippi were the most affected states by Hurricane Katrina in terms of statewide damage,[14] we expect to find a smaller increase in household credit-to-GDP among the states with the highest long-term orientation and risk aversion scores within this sub-sample. However, before we can test this hypothesis, we first have to establish empirically that Hurricane Katrina was truly an exogenous shock to inequality and subsequently to household credit in these four states. We therefore divide our entire U.S. state-level sample into a treatment group consisting of Alabama, Florida, Louisiana, and Mississippi and a control group, which is composed of the remaining 46 states. We code 2004 as the pre-treatment year and 2005 as the post-treatment year for the income inequality difference-in-difference regression since we expect to observe an almost immediate expansion in income inequality caused by disproportionately high instantaneous wage losses of the poor. This can be explained by the fact that rich people are more able to afford to live in areas historically less affected by natural disasters than

[13] U.S. Department of Defense: https://dod.defense.gov/News/Article/Article/615149/remembering-hurricane-katrina-a-decade-later/

[14] GO Zone Gateway: http://www.gozonegateway.com/articles/what-is-the-go-zone-part1/

poor people are (Yamamura, 2015). Accordingly, Logan (2006) finds that the poor appear to have suffered higher levels of damage in the city of New Orleans inflicted by Hurricane Katrina. This leads to a more unequal income distribution given that the poor are more likely to be injured or impaired by their damaged property, which leaves them unable to work and earn their wages (Yamamura, 2015).

As for the household credit-to-GDP regression, we code 2005 as the pre-treatment year and 2006 as the post-treatment year. This is based on the assumption that it will take a certain amount of time for the affected households to be able to assess the damage to their property and hence negotiate various loan agreements with their banks for rebuilds and repairs. The results presented in Table 2 and Table 4 further strengthen the validity of this assumption. They demonstrate that a shock to income inequality has only a delayed effect on household credit. Consequently, we estimate the following two difference-in-difference regressions:

$$\Delta \mathit{Top\ 1\%\ share}_{i,t} = \alpha_{i,t} + \beta_1 \mathit{Treat}_i + \beta_2 \mathit{Post}_t + \beta_3(\mathit{Treat}_i \times \mathit{Post}_t) + \mathbf{X}' + e_{i,t} \qquad (2)$$

$$\Delta \mathit{Credit/GDP}_{i,t} = \alpha_{i,t} + \beta_1 \mathit{Treat}_i + \beta_2 \mathit{Post}_t + \beta_3(\mathit{Treat}_i \times \mathit{Post}_t) + \mathbf{X}' + e_{i,t} \qquad (3)$$

The results for both regressions are reported in Table 5. They reveal that the change in income inequality (household credit as a ratio of GDP) was greater in the affected states from 2004 to 2005 (2005 to 2006) compared to all other states. The significant coefficient on the interaction in Column (2) shows that, on average, Katrina increased income inequality by about 2.29% in Alabama, Florida, Louisiana, and Mississippi. This result is in line with Bui et al. (2014) who find that natural disasters tend to worsen the income distribution among households. According to the interaction term in Column (4), Katrina evoked an average increase of about 12.09% in the household credit-to-GDP ratio in the affected states.

[Table 5 about here.]

To ensure that these results are not driven by a selection bias, we additionally perform propensity score matching (PSM) as a robustness test. The PSM approach involves pairing treatment and control states based on similar predetermined observable characteristics (Dehejia and Wahba, 2002). The control group reduces from 46 to four states: Arizona, Kentucky, New Mexico, and West Virginia. However, comparability between the treatment and the control group rises, as becomes evident when comparing Table A10 and Table A11 in our appendix. The estimation results of the quasi-natural experiment based on the PSM approach are reported in Table A12 in our appendix. The coefficients of interest remain noticeably consistent in magnitude as well as in significance.

Having identified that Hurricane Katrina has been an exogenous shock to income inequality and thereafter to household credit in the states that were most affected by its destruction, we can now turn to our initial hypothesis. Accordingly, we focus on the long-term orientation and risk aversion scores of Alabama, Florida, Louisiana, and Mississippi. Unfortunately, the long-term orientation scores for these states are essentially indistinguishable from one another. Thus, we are forced to only consider the risk aversion dimension, proxied by the health care coverage rate. Alabama has the highest risk aversion score in 2004, consequently, it becomes the new treatment group and the three remaining states become the new control group. Table 6 reports the estimation results of Equation (3) for this sub-sample. They yield supporting evidence for the hypothesis that a relatively higher degree of risk aversion lowers the impact of a shock to income inequality on household credit.

[Table 6 about here.]

6 Credit Growth and Banking Crises

Thus far, we have identified that time and risk preferences possess a moderating impact on a cross-country as well as on a U.S. state-level basis. These findings continue to be statistically significant even when controlling for formalized governance settings or other culture dimensions. From a macroeconomic perspective, the fact that household credit has been shown to be a significant determinant of banking crises suggests further examination. Similar to Büyükkarabacak and Valev (2010) and Schularick and Taylor (2012), we analyze whether the relation between credit growth and banking crises also holds for our international sample. This allows us to establish a link between income inequality, household credit, and ultimately the often resulting crises.

In line with Bordo and Meissner (2012) and Schularick and Taylor (2012), we estimate the following model:

$$\text{Pr}(\text{Banking crisis}_{i,t}) = f\left\{\sum_{p=1}^{5}\Delta(Credit/GDP)_{i,t-p} + \mathbf{X}' + z_i + e_{i,t}\right\}, \tag{4}$$

whereas subscripts i and t indicate countries and years, and $e_{i,t}$ resembles an idiosyncratic error term for each country and each year. Following Schularick and Taylor (2012) and Kirschenmann et al. (2016), we only use country fixed effects, labeled as z_i. Δ denotes the annual change; Credit/GDP describes the household credit-to-GDP ratio; and $\mathbf{X}'$ is a set of control variables. As in Schularick and Taylor (2012), the lag length for the household credit measure, p, is set to five. For the dependent variable, we employ binary coded financial crises episodes collected by Jordà et al. (2017). A banking crisis period is defined as a scenario in which a country's financial sector experiences bank runs, substantial increases in default rates accompanied by high capital losses evoking government interventions, bankruptcy or forced mergers of financial institutions (Jordà et al., 2017).

[Table 7 about here.]

Table 7 presents the results of some simple variants of Equation (4). To obtain a uniform lag structure, we include the first five annual lags of any independent variable. Column (1) presents a Linear Probability Model (LPM) without control variables. Column (2) then adds our control variables with five annual lags to the OLS model. Both regressions indicate that household credit expansions over the previous five years are strongly associated with a heightened risk of a banking crisis. A one standard deviation increase of about 2.5% in our first difference credit measure raises the probability that a crisis occurs in the third year after the shock by about 2.75%.

However, there are well-known shortcomings with the LPM, in particular that the predicted values of the dependent variable are not constrained to the unit interval corresponding to probability outcomes. Consequently, we shift to a pooled logit model in Columns (3) and (4). Column (3) displays the results of the logit model without our set of control variables. In Column (4), we add the control variables to the regression. In line with Bordo and Meissner (2012) and Schularick and Taylor (2012), our findings show that an increase in the household credit-to-GDP ratio over the previous five years significantly raises the probability of the occurrence of a banking crisis. The average marginal effect of 0.012 for $\Delta(\text{Household credit/GDP})_{i,t-3}$ implies that a one standard deviation increase of about 2.5% in the credit measure raises the probability that a crisis occurs in the third year after the shock by about 3% on average.

Finally, we note that all variants presented in Table 7 have predictive power, as judged by the AUROC value. AUROC stands for the area under the ROC curve, which plots the true positive rate against the false positive rate. An AUROC value of 0.5 denotes the worst classifier (indistinguishable from a coin toss) and 1 denotes the best classifier. Given that all our regressions have an AUROC value of above 0.79, they can therefore be regarded as having predictive power versus a coin toss (Schularick and Taylor, 2012). In particular, it implies that given a randomly selected country within a crisis period and a randomly selected country without experiencing a crisis, there is a 79% probability that our models indicates the country within a crisis period correctly as such.

7 Conclusion

In this paper, we contribute to the discussion about the impact of income inequality on household credit growth. We analyze how the relation between inequality and credit is moderated by cultural dissimilarities – long-termism and risk aversion – across different countries.

Using an international sample of 16 OECD countries over 47 years, we find empirical evidence that household credit growth reacts less sensitive to increasing income inequality in long-term oriented and highly risk averse societies. We replicate these results using

U.S. state-level data. In line with our international findings, an increase in inequality is associated with a smaller rise in household credit in states with a more long-term oriented and more risk averse population. We show that household credit expansions increase the probability of banking crises. These results advance our understanding of why rising income inequality leads to banking crises in some countries but not in others.

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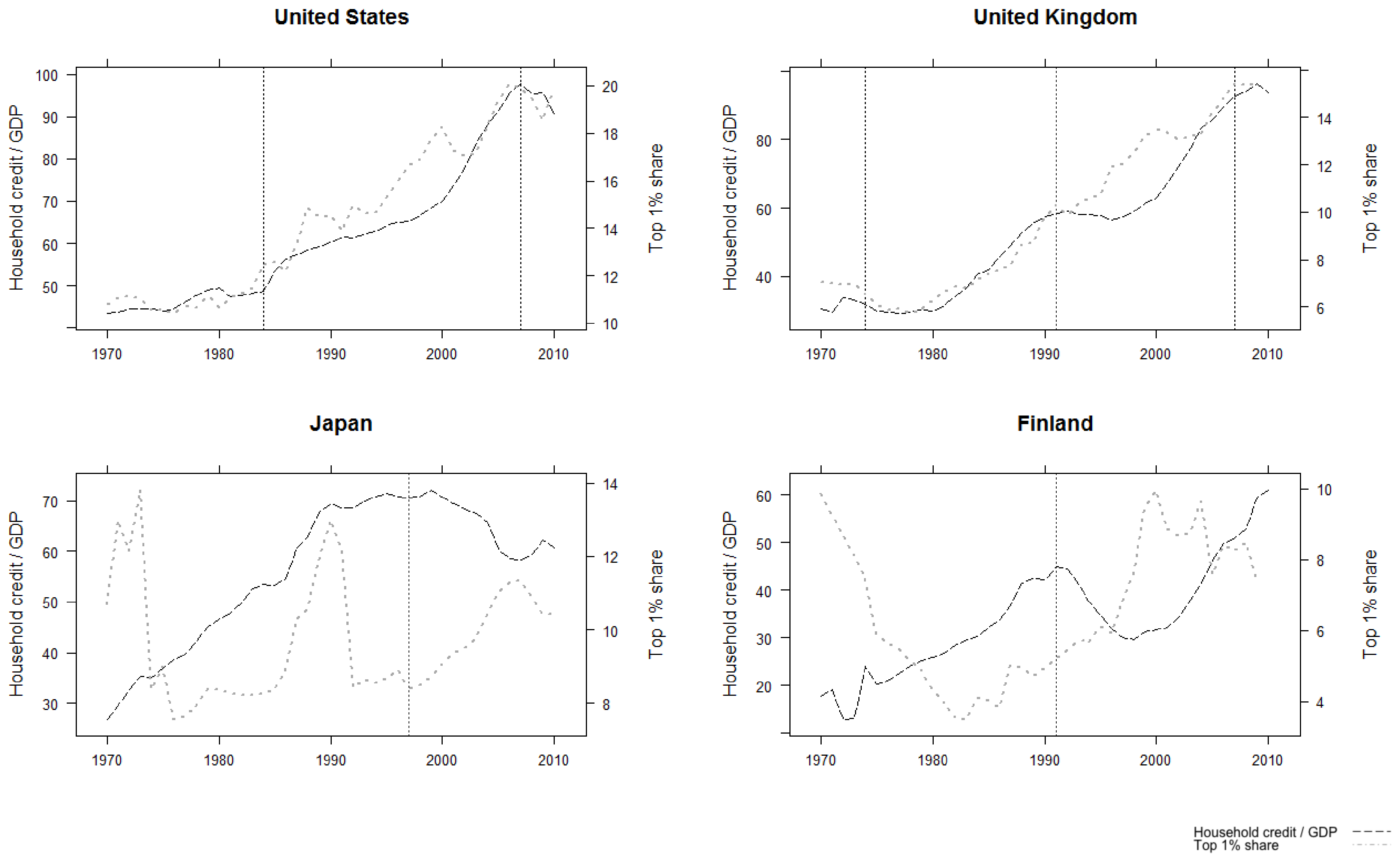

Figure 1. Income Inequality, Household Credit-to-GDP, and Banking Crisis: Selected Countries, 1970-2010

Table 1. Summary Statistics - International

Variable	N	Mean	St. Dev.	Min	Max
Household credit/GDP	631	57.576	27.332	7.600	139.400
Top 1% share	555	9.066	3.198	3.489	20.779
LTO (Hofstede)	16	50.438	19.984	21	88
Health care coverage	555	97.504	6.287	61	100
Real GDP per capita	631	18.980	5.366	7.733	36.359
Current account/GDP	631	0.471	4.787	−17.859	16.232
Broad money/GDP	631	69.786	25.136	38.129	174.810
Real short-term interest rate	631	1.636	2.927	−10.204	10.792
Creditor rights (Djankov)	631	2.044	1.038	0	4

Note: This table shows summary statistics for each variable considered in our international analysis. Household credit-to-GDP data are provided by the Bank for International Settlements (BIS). The Top 1% share is retrieved from the World Inequality Database. We acquire our long-term orientation proxy, LTO (Hofstede), from the Hofstede Insights database. The risk aversion proxy is a measure of health care coverage, provided by the OECD database. The calculations of Real GDP per capita, (Current account/GDP), (Broad money/GDP), and Real short-term interest rate are based on the Jordà-Schularick-Taylor Macrohistory Database, compiled by Jordà et al. (2017). Real GDP per capita is stated in thousands of national currency per international dollar. Creditor rights are obtained from Djankov et al. (2007).

Table 2. Baseline Regression Results

	Dependent variable: Δ(Household credit/GDP)$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Δ(Household credit/GDP)$_{i,t-1}$		0.561***		0.570***	0.563***
		(0.074)		(0.077)	(0.076)
Δ(Household credit/GDP)$_{i,t-2}$		0.031		0.036	0.030
		(0.024)		(0.025)	(0.024)
ΔTop 1% share$_{i,t-1}$	0.221	0.459*	3.931*	3.389**	3.169**
	(0.226)	(0.249)	(2.330)	(1.483)	(1.255)
ΔTop 1% share$_{i,t-2}$	0.482***	0.514**	0.512	−1.361	−1.532
	(0.180)	(0.225)	(2.787)	(1.743)	(1.475)
LTO$_i$ × ΔTop 1% share$_{i,t-1}$	−0.010***	−0.014***			−0.013***
	(0.003)	(0.005)			(0.005)
LTO$_i$ × ΔTop 1% share$_{i,t-2}$	−0.010***	−0.008*			−0.008**
	(0.003)	(0.004)			(0.004)
Health care cov.$_{i,t-1}$ × ΔTop 1% share$_{i,t-1}$			−0.043*	−0.036**	−0.028**
			(0.023)	(0.015)	(0.013)
Health care cov.$_{i,t-2}$ × ΔTop 1% share$_{i,t-2}$			−0.005	0.015	0.021
			(0.028)	(0.018)	(0.016)
Creditor rights$_{i,t-1}$ × ΔTop 1% share$_{i,t-1}$		0.184*		0.094	0.212**
		(0.096)		(0.116)	(0.091)
Creditor rights$_{i,t-2}$ × ΔTop 1% share$_{i,t-2}$		0.081		−0.018	0.054
		(0.104)		(0.104)	(0.104)
Creditor rights$_{i,t-1}$		0.190		0.185	0.186
		(0.148)		(0.137)	(0.146)
ΔReal GDP per capita$_{i,t-1}$		1.245***		1.227***	1.212***
		(0.245)		(0.248)	(0.233)
Δ(Current account/GDP)$_{i,t-1}$		0.045		0.063	0.048
		(0.060)		(0.060)	(0.059)
Δ(Broad money/GDP)$_{i,t-1}$		−0.016		−0.019	−0.013
		(0.039)		(0.039)	(0.038)
ΔReal short term interest rate$_{i,t-1}$		−0.012		−0.009	−0.011
		(0.032)		(0.030)	(0.031)
Time and country fixed effects	Yes	Yes	Yes	Yes	Yes
Number of countries	16	16	16	16	16
Observations	523	523	523	523	523
Adjusted R^2	0.016	0.407	0.090	0.400	0.408

Note: This table contains estimation results of Equation 1 for our international dataset. The dependent variable is the annual change in household credit-to-GDP. ΔTop 1% share is the change in the share of national income going to the Top 1% income earners. LTO is our long-term orientation proxy, provided by the Hofstede Insights database. The risk aversion proxy is the health care coverage rate, retrieved from the OECD database. The calculations of ΔReal GDP per capita, Δ(Current account/GDP), Δ(Broad money/GDP), and ΔReal short-term interest rate are based on the Jordà-Schularick-Taylor Macrohistory Database. Real GDP per capita is stated in thousands of national currency per international dollar. Creditor rights are obtained from Djankov et al. (2007) Robust standard errors are reported in parentheses. *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.

Table 3. Summary Statistics – U.S.

Variable	N	Mean	St. Dev.	Min	Max
Household credit/GDP	650	90.826	21.006	46.733	161.145
Top 1% share	600	17.876	4.486	10.867	36.040
Anti-nationalism	600	99.488	0.126	99.005	99.786
Health care coverage	600	86.403	3.977	74.497	96.700
Real GDP per capita	600	46.862	8.726	30.509	73.505
Real wages per capita	600	20.082	3.532	13.435	31.365

Note: This table shows summary statistics for the main variables of interest to our U.S. state-level regression analysis. Household credit per capita data are provided in the State Level Household Debt Statistics by the Federal Reserve Bank of New York. The household credit per capita measure is then scaled by nominal GDP per capita to obtain our dependent variable. Nominal and real GDP per capita as well as nominal wages are accessed from the Bureau of Economic Analysis Regional Accounts. Nominal wages are then deflated using the annual U.S. inflation rate from the World Bank and are scaled by the annual U.S. state population from the U.S. Census Bureau (both retrieved from the Federal Reserve Bank of St. Louis). Real GDP and real wages per capita are presented in thousands of U.S. dollars. The Top 1% share is retrieved from the World Inequality Database. The anti-nationalism variable is obtained by subtracting yearly non-prior service enlisted accessions to the U.S. military as a share of U.S. state population from 100. The number of enlisted accessions are aquired from the Office of the Under Secretary of Defense, Personnel and Readiness. The health care coverage rate is provided by the U.S. Census Bureau.

Table 4. Baseline Regression Results – U.S.

	Dependent variable: Δ(Household credit/GDP)$_{i,t}$			
	(1)	(2)	(3)	(4)
Δ(Household credit/GDP)$_{i,t-1}$		0.415***		0.413***
		(0.074)		(0.072)
Δ(Household credit/GDP)$_{i,t-2}$		0.133***		0.139***
		(0.045)		(0.045)
ΔTop 1% share$_{i,t-1}$	−85.159	29.793	0.499	2.062*
	(74.169)	(99.590)	(1.313)	(1.152)
ΔTop 1% share$_{i,t-2}$	186.124*	156.937**	4.578**	4.387***
	(95.777)	(64.268)	(2.256)	(1.565)
Anti-nationalism$_{i,t-1}$ × ΔTop 1% share$_{i,t-1}$	0.856	−0.299		
	(0.745)	(1.000)		
Anti-nationalism$_{i,t-2}$ × ΔTop 1% share$_{i,t-2}$	−1.869*	−1.577**		
	(0.961)	(0.645)		
Health care coverage$_{i,t-1}$ × ΔTop 1% share$_{i,t-1}$			−0.006	−0.024*
			(0.016)	(0.014)
Health care coverage$_{i,t-2}$ × ΔTop 1% share$_{i,t-2}$			−0.052**	−0.052***
			(0.026)	(0.018)
ΔReal GDP per capita$_{i,t-1}$		0.859***		0.896***
		(0.256)		(0.250)
ΔReal wages per capita$_{i,t-1}$		0.899*		0.922
		(0.535)		(0.566)
Time and state fixed effects	Yes	Yes	Yes	Yes
Observations	500	500	500	500
Number of states	50	50	50	50
Adjusted R^2	0.028	0.275	0.022	0.281

Note: This table contains estimation results of the fixed effects model for our U.S. state-level dataset. The dependent variable is the annual change in household credit-to-GDP. ΔTop 1% share is the change in the share of state income going to the Top 1% income earners. Anti-nationalism is the long-term orientation proxy, obtained by subtracting yearly non-prior service enlisted accessions to the U.S. military as a share of U.S. state population from 100. Health care coverage rate is the risk aversion proxy. Real GDP per capita and real wages per capita are stated in thousands of U.S. dollars. Robust standard errors are reported in parentheses. *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.

Table 5. Difference-in-Difference Regression Results – Hurricane Katrina

	Dependent variable:			
	ΔTop 1% share$_{i,t}$ (2004–2005)		Δ(Household credit/GDP)$_{i,t}$ (2005–2006)	
	(1)	(2)	(3)	(4)
Constant	1.824***	2.253***	2.167***	−0.232
	(0.166)	(0.318)	(0.430)	(0.938)
Treat$_i$	−0.073	−0.495	−8.279**	−7.845**
	(1.253)	(1.147)	(4.147)	(3.990)
Post$_t$	−0.173	−0.991**	2.116***	3.320***
	(0.162)	(0.489)	(0.480)	(1.031)
Treat$_i$ × Post$_t$	1.826**	2.292***	13.124***	12.094***
	(0.839)	(0.845)	(3.053)	(2.994)
ΔReal GDP per capita$_{i,t-1}$		−0.173		0.829
		(0.144)		(0.527)
ΔReal wages per capita$_{i,t-1}$		0.673		4.034
		(0.609)		(3.033)
ΔUnemployment$_{i,t-1}$		−0.919**		0.257
		(0.448)		(0.909)
ΔMinimum wage$_{i,t-1}$		−0.733**		0.739
		(0.290)		(1.710)
Number of states	50	50	50	50
Observations	100	100	100	100
Adjusted R^2	0.060	0.136	0.260	0.323

Note: This table contains estimation results of Equations 2 and 3 for our quasi-natural experiment. The dependent variable is the change in the Top 1% income share in the first and second column. In the third and fourth column, the dependent variable is the annual change in household credit-to-GDP. The year of the income inequality shock is 2004. The shock to household credit is lagged by one year. The treatment group is composed of Alabama, Florida, Louisiana, and Mississippi. The control group consists of the remaining 46 U.S. states. Real GDP per capita and real wages per capita are stated in thousands of U.S. dollars. ΔUnemployment is the change in the state's unemployment rate in percentage points. ΔMinimum wage is the change in the state's minimum wage in U.S. dollars. Robust standard errors are reported in parentheses. *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.

Table 6. Difference-in-Difference Regression Results – Hurricane Katrina (Sub-Sample)

	Dependent variable: Δ(Household credit/GDP)$_{i,t}$ (2005–2006)
Constant	-6.885
	(5.426)
Treat$_i$	3.090
	(5.426)
Post$_{t-1}$	17.199***
	(3.322)
Treat$_i$ $\times$ Post$_{t-1}$	-7.840^{**}
	(3.322)
Number of states	4
Observations	8
Adjusted R^2	0.322

Note: This table contains estimation results of Equation 3 for our sub-sample of the most affected states by Hurricane Katrina – Alabama, Florida, Louisiana, and Mississippi. The dependent variable is the annual change in household credit-to-GDP. The year of the household credit shock is 2005. The treatment group consists of Alabama – the state with the highest risk aversion score. The control group is composed of the remaining three states. Robust standard errors are reported in parentheses. *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.

Table 7. Banking Crisis Prediction – OLS and Logit Estimates

	Dependent variable: Banking crisis$_{i,t}$			
	OLS		*Logit*	
	(1)	(2)	(3)	(4)
Δ(Household credit/GDP)$_{i,t-1}$	-0.006^{*}	-0.011^{**}	-0.146	-0.366^{**}
	(0.003)	(0.005)	(0.106)	(0.176)
			[-0.0047]	[-0.0098]
Δ(Household credit/GDP)$_{i,t-2}$	0.0003	-0.002	0.051	-0.310^{**}
	(0.004)	(0.005)	(0.097)	(0.143)
			[0.0016]	[-0.0083]
Δ(Household credit/GDP)$_{i,t-3}$	0.011^{**}	0.011^{**}	0.308^{***}	0.448^{**}
	(0.005)	(0.005)	(0.090)	(0.200)
			[0.0099]	[0.0120]
Δ(Household credit/GDP)$_{i,t-4}$	0.003	0.008^{**}	0.079	0.439^{**}
	(0.003)	(0.004)	(0.083)	(0.202)
			[0.0025]	[0.0118]
Δ(Household credit/GDP)$_{i,t-5}$	0.005	0.006	0.183^{*}	0.159
	(0.003)	(0.005)	(0.095)	(0.173)
			[0.0059]	[0.0042]
Country fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes
Observations	535	535	535	535
Number of countries	16	16	16	16
AUROC	0.7903	0.8712	0.7956	0.9128
Adjusted R^2 / Pseudo R^2	0.0068	0.0181	0.1480	0.3683

Note: This table contains estimation results of Equation 4 for our international dataset. The dependent variable a is a dummy equal to 1 when a banking crisis occurred according to the Jordà-Schularick-Taylor Macrohistory Database. Δ(Household credit/GDP) is the annual change in household credit-to-GDP. Our set of control variables consists of the first five lags of ΔReal GDP per capita, Δ(Current account/GDP), Δ(Broad money/GDP), ΔReal short-term interest rate, and Creditor rights. AUROC stands for the area under the ROC curve and summarizes the discrimination ability of a model. Values of Adjusted R^2 belong to the OLS regressions and those of Pseudo R^2 to the Logit regressions. Robust standard errors are reported in parentheses. Average marginal effects are reported in square brackets. *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.

Appendix for "Inequality, Credit, and Crises: The Role of Culture"

A.1 Analysis of the Steady-State Income Relationship of Kumhof et al. (2015)

In their DSGE framework, Kumhof et al. (2015) point out that an increase in income inequality – more specifically an increase in top earners' output share ($\overline{z}$) – leads to a rising steady-state level of debt ($\bar{b}$). To show this effect, Kumhof et al. (2015) differentiate the steady-state relationship with respect to the top earners' output share ($\overline{z}$) and obtain the following term:

$$\frac{d\ log(\bar{b})}{d\ log(\overline{z})} = \frac{\frac{1}{\sigma}\left(\overline{y}\,\overline{z}\frac{1}{\chi}\right)}{\frac{1}{\eta}\frac{\bar{b}\frac{(1-\chi)}{\chi}}{1+\frac{(1-\chi)}{\chi}}\overline{c}^{\tau} - \frac{1}{\sigma}(1-\beta_b)\frac{(1-\chi)}{\chi}}, \tag{5}$$

where $\overline{y}$ is the aggregate steady-state output, χ is the population share of top earners, $\overline{c}^{\tau}$ is the steady-state top earners' per capita consumption, σ and η parameterize the curvature of the utility function with respect to consumption and wealth, and β_b is the discount factor of bottom earners.

For any plausible calibration this term is positive, which implies that rising income inequality increases the steady-state equilibrium level of debt. We can use Equation 5 to show that long-term oriented societies react less sensitive to an income inequality shock than short-term oriented societies. Long-term oriented societies have a higher discount factor (β_b^{LT}) than short-term oriented societies because they value future consumption higher (β_b^{ST}).[15] To demonstrate the varying impact of increasing income inequality in long-term and short-term oriented societies, we use β_b^{LT} and β_b^{ST} in Equation 5 and compare the terms on the assumption that $\beta_b^{LT} > \beta_b^{ST}$.

[15]The lifetime utility is given by $E_t \sum_{k\geq 0}^{\infty} \beta_b^k \left\{ \frac{\left(c_{t+k}^b\right)^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} \right\}$.

$$\frac{\frac{1}{\sigma}\left(\overline{y}\,\overline{z}\frac{1}{\chi}\right)}{\frac{1}{\eta}\frac{\bar{b}\frac{(1-\chi)}{\chi}}{1+\frac{(1-\chi)}{\chi}}\overline{c}^{\tau}-\frac{1}{\sigma}(1-\beta_b^{LT})\frac{(1-\chi)}{\chi}} < \frac{\frac{1}{\sigma}\left(\overline{y}\,\overline{z}\frac{1}{\chi}\right)}{\frac{1}{\eta}\frac{\bar{b}\frac{(1-\chi)}{\chi}}{1+\frac{(1-\chi)}{\chi}}\overline{c}^{\tau}-\frac{1}{\sigma}(1-\beta_b^{ST})\frac{(1-\chi)}{\chi}}$$

$$\frac{\frac{1}{\eta}\frac{\bar{b}\frac{(1-\chi)}{\chi}}{1+\frac{(1-\chi)}{\chi}}\overline{c}^{\tau}-\frac{1}{\sigma}(1-\beta_b^{LT})\frac{(1-\chi)}{\chi}}{\frac{1}{\sigma}\left(\overline{y}\,\overline{z}\frac{1}{\chi}\right)} > \frac{\frac{1}{\eta}\frac{\bar{b}\frac{(1-\chi)}{\chi}}{1+\frac{(1-\chi)}{\chi}}\overline{c}^{\tau}-\frac{1}{\sigma}(1-\beta_b^{ST})\frac{(1-\chi)}{\chi}}{\frac{1}{\sigma}\left(\overline{y}\,\overline{z}\frac{1}{\chi}\right)}$$

$$-\frac{1}{\sigma}(1-\beta_b^{LT})\frac{(1-\chi)}{\chi} > -\frac{1}{\sigma}(1-\beta_b^{ST})\frac{(1-\chi)}{\chi}$$

$$(1-\beta_b^{LT}) < (1-\beta_b^{ST})$$

$$\beta_b^{LT} > \beta_b^{ST}$$

This transformation implies that the effect of income inequality on the steady-state equilibrium level of debt is weaker in long-term than in short-term oriented societies.

A.2 Description of Variables

Variable	Type	Description
I. Culture Dimensions		
Power Distance Index *(PDI)*	Cross-section	Degree of acceptance and expectations of unequally distributed power within society, where a higher score indicates a higher level of acceptance of unequal distributed power and a lower level reflects a society that feels the urge to dissolve inequalities of power. Source: Hofstede et al. (2010)
Individualism versus Collectivism *(IDV)*	Cross-section	Dimension that reflects a society's preference regarding the social framework, where individualism indicates a preference for a loose framework and collectivism for a tight framework. Source: Hofstede et al. (2010)
Masculinity versus Feminity *(MAS)*	Cross-section	Dimension that reflects a society's preference for achievements, where masculinity implies a more competitive- and feminity a more consensus-oriented society. Source: Hofstede et al. (2010)
Uncertainty Avoidance Index *(UAI)*	Cross-section	Dimension that reflects the attitude of members of society towards uncertainty and ambiguity, where a higher level expresses intolerance of unorthodox behavior and ideas. Source: Hofstede et al. (2010)
Long Term Orientation versus Short Term Normative Orientation *(LTO)*	Cross-section	Dimension that reflects the attitude of a society towards societal challenges, where a higher level implies the ability to adopt to changed conditions more easily. Source: Hofstede et al. (2010)
Indulge versus Restraint *(IND)*	Cross-section	Dimension that reflects the attitude of a society towards allowing relatively free gratification of basic human drives, where a higher score indicates restraint and suppression of gratification and a lower level reflects indulgance. Source: Hofstede et al. (2010)

II. Worldwide Governance Indicators		
Voice and Accountability	Cross-section & annual time-series	Dimension that captures the extent to which a country's citizens are able to engage in democratic activities such as taking part in electing government officials, as well as free media and press. Source: (Kaufmann et al., 2011)
Political Stability and Absence of Violence/Terrorism	Cross-section & annual time-series	Dimension that reflects the perceived probability of political instability and/or politically-motivated violence such as terrorism. Source: (Kaufmann et al., 2011)
Government Effectiveness	Cross-section & annual time-series	Dimension that captures the perceived quality of public and civil services, the quality of policy implementations, and the integrity of the government's commitment to such policies. Source: (Kaufmann et al., 2011)
Regulatory Quality	Cross-section & annual time-series	Dimension that reflects the ability of the government to provide and enforce sound policies and regulations concerning the development of the private sector. Source: (Kaufmann et al., 2011)
Rule of Law	Cross-section & annual time-series	Dimension that reflects the degree to which agents follow the rules of society, in particular the quality of contract enforcement, property rights, police and court and the likelihood of crime and violence. Source: (Kaufmann et al., 2011)
Control of Corruption	Cross-section & annual time-series	Dimension that reflects the perceived misusage of public power for private gain. Source: (Kaufmann et al., 2011)

A.3 Additional Tables

Table A1:	This table shows the international baseline regression results with the Top 10% income share as an alternative proxy for income inequality.
Table A2:	This table shows the international baseline regression results with the real long-term interest rate and the natural logarithm of real GDP per capita as additional control variables.
Table A3:	This table shows the international baseline regression results with a second lag of each control variable.
Table A4:	This table shows the international baseline regression results with alternative proxies for long-termism and risk aversion based on questions from the World Values Survey.
Table A5:	This table shows the international baseline regression results with additional cultural dimensions from the Hofstede Insights database.
Table A6:	This table shows the international baseline regression results with the inclusion of the Worldwide Governance Indicators (WGI), which are published by the World Bank (Kaufmann et al., 2011).
Table A7:	This table shows the U.S. state-level baseline regression results with the Top 10% income share as an alternative proxy for income inequality.
Table A8:	This table shows the two-step system GMM estimation for the U.S. state-level sample with anti-nationalism as a long-term orientation proxy.

Table A9:	This table shows the two-step system GMM estimation for the U.S. state-level sample with the health care coverage rate as a risk aversion proxy.
Table A10:	This table shows U.S. state-level summary statistics for the main variables of interest for the quasi-natural experiment.
Table A11:	This table shows U.S. state-level summary statistics for the main variables of interest for the quasi-natural experiment after performing propensity score matching.
Table A12:	This table shows U.S. state-level regression results for the quasi-natural experiment after performing propensity score matching.

Table A1. Baseline Regression Results with Top 10% Income Share

	Dependent variable: Δ(Household credit/GDP)$_{i,t}$		
	(1)	(2)	(3)
Δ(Household credit/GDP)$_{i,t-1}$	0.662***	0.676***	0.666***
	(0.049)	(0.051)	(0.051)
Δ(Household credit/GDP)$_{i,t-2}$	0.017	0.015	0.014
	(0.031)	(0.033)	(0.032)
ΔTop 10% share$_{i,t-1}$	0.250	4.239***	4.206***
	(0.234)	(1.337)	(1.174)
ΔTop 10% share$_{i,t-2}$	0.453**	−1.390	−1.474
	(0.206)	(1.069)	(0.898)
LTO$_i$ $\times$ ΔTop 10% share$_{i,t-1}$	−0.008**		−0.007**
	(0.004)		(0.004)
LTO$_i$ $\times$ ΔTop 10% share$_{i,t-2}$	−0.006**		−0.007**
	(0.003)		(0.003)
Health care cov.$_{i,t-1}$ $\times$ ΔTop 10% share$_{i,t-1}$		−0.044***	−0.040***
		(0.014)	(0.013)
Health care cov.$_{i,t-2}$ $\times$ ΔTop 10% share$_{i,t-2}$		0.015	0.020
		(0.011)	(0.010)
Creditor rights$_{i,t-1}$ $\times$ ΔTop 10% share$_{i,t-1}$	0.202**	0.168**	0.230***
	(0.086)	(0.081)	(0.081)
Creditor rights$_{i,t-2}$ $\times$ ΔTop 10% share$_{i,t-2}$	0.060	−0.020	0.044
	(0.069)	(0.065)	(0.067)
Creditor rights$_{i,t-1}$	−0.080	−0.062	−0.083
	(0.159)	(0.167)	(0.155)
ΔReal GDP per capita$_{i,t-1}$	1.349***	1.328***	1.300***
	(0.240)	(0.238)	(0.223)
Δ(Current account/GDP)$_{i,t-1}$	0.075	0.089	0.077
	(0.061)	(0.061)	(0.061)
Δ(Broad money/GDP)$_{i,t-1}$	−0.019	−0.024	−0.017
	(0.039)	(0.038)	(0.039)
ΔReal short term interest rate$_{i,t-1}$	−0.007	0.0001	−0.005
	(0.034)	(0.033)	(0.033)
Time and country fixed effects	Yes	Yes	Yes
Number of countries	16	16	16
Observations	503	503	503
Adjusted R^2	0.494	0.492	0.497

Note: The dependent variable is the annual change in household credit-to-GDP. ΔTop 10% share is the change in the share of national income going to the Top 10% income earners. LTO is our long-term orientation proxy, provided by the Hofstede Insights database. The risk aversion proxy is the health care coverage rate, retrieved from the OECD database. The calculations of ΔReal GDP per capita, Δ(Current account/GDP), Δ(Broad money/GDP), and ΔReal short-term interest rate are based on the Jordà-Schularick-Taylor Macrohistory Database. Real GDP per capita is stated in thousands of national currency per international dollar. Credit rights are mean-centered and are obtained from Djankov et al. (2007). *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.

Table A2. Regression Results with the Real Long-term Interest Rate and the Natural Logarithm of Real GDP per Capita

	Dependent variable: Δ(Household credit/GDP)$_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ(Household credit/GDP)$_{i,t-1}$	0.558***	0.566***	0.560***	0.561***	0.569***	0.563***
	(0.074)	(0.077)	(0.075)	(0.073)	(0.076)	(0.075)
Δ(Household credit/GDP)$_{i,t-2}$	0.037	0.042*	0.035	0.030	0.036	0.029
	(0.024)	(0.025)	(0.023)	(0.023)	(0.024)	(0.023)
ΔTop 1% share$_{i,t-1}$	0.483*	3.483**	3.271***	0.507*	4.093***	3.857***
	(0.255)	(1.475)	(1.245)	(0.261)	(1.581)	(1.336)
ΔTop 1% share$_{i,t-2}$	0.518**	−1.233	−1.393	0.506**	−1.100	−1.273
	(0.225)	(1.738)	(1.473)	(0.233)	(1.781)	(1.512)
LTO$_i$ × ΔTop 1% share$_{i,t-1}$	−0.014***		−0.014***	−0.014***		−0.014***
	(0.005)		(0.005)	(0.005)		(0.005)
LTO$_i$ × ΔTop 1% share$_{i,t-2}$	−0.007*		−0.008*	−0.007*		−0.008*
	(0.004)		(0.004)	(0.004)		(0.004)
Health care cov.$_{i,t-1}$ × ΔTop 1% share$_{i,t-1}$		−0.037**	−0.028**		−0.043***	−0.034**
		(0.015)	(0.013)		(0.016)	(0.014)
Health care cov.$_{i,t-2}$ × ΔTop 1% share$_{i,t-2}$		0.014	0.019		0.012	0.018
		(0.018)	(0.016)		(0.018)	(0.016)
Creditor rights$_{i,t-1}$ × ΔTop 1% share$_{i,t-1}$	0.181*	0.087	0.209**	0.173*	0.083	0.207**
	(0.096)	(0.120)	(0.091)	(0.100)	(0.120)	(0.094)
Creditor rights$_{i,t-2}$ × ΔTop 1% share$_{i,t-2}$	0.092	−0.005	0.066	0.072	−0.022	0.046
	(0.106)	(0.105)	(0.106)	(0.104)	(0.104)	(0.104)
Creditor rights$_{i,t-1}$	0.172	0.169	0.168	0.192	0.184	0.187
	(0.142)	(0.132)	(0.139)	(0.150)	(0.140)	(0.148)
ΔReal GDP per capita$_{i,t-1}$	1.289***	1.266***	1.255***			
	(0.251)	(0.252)	(0.237)			
ΔLn(Real GDP per capita)$_{i,t-1}$				20.520***	20.143***	20.159***
				(3.888)	(3.890)	(3.672)
Δ(Current account/GDP)$_{i,t-1}$	0.041	0.059	0.044	0.046	0.064	0.050
	(0.058)	(0.059)	(0.058)	(0.060)	(0.060)	(0.059)
Δ(Broad money/GDP)$_{i,t-1}$	−0.019	−0.021	−0.016	−0.013	−0.016	−0.010
	(0.039)	(0.039)	(0.038)	(0.039)	(0.039)	(0.038)
ΔReal short term interest rate$_{i,t-1}$	−0.082**	−0.071*	−0.080**	−0.014	−0.012	−0.013
	(0.038)	(0.039)	(0.036)	(0.032)	(0.030)	(0.031)
ΔReal long term interest rate$_{i,t-1}$	0.116***	0.103***	0.115***			
	(0.032)	(0.032)	(0.032)			
Time and country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	16	16	16	16	16	16
Observations	523	523	523	523	523	523
Adjusted R^2	0.409	0.400	0.409	0.404	0.396	0.405

Note: The dependent variable is the annual change in household credit-to-GDP. The real long-term interest rate represents the nominal long-term interest rate adjusted for inflation, taken from the Jordà-Schularick-Taylor Macrohistory Database. ΔLn(Real GDP per capita) represents the annual change in the natural logarithm of real GDP per capita. Robust standard errors are reported in parentheses. *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.

Table A3. Regression Results with the Second Lag of Each Control Variable

	Dependent variable: Δ(Household credit/GDP)$_{i,t}$		
	(1)	(2)	(3)
Δ(Household credit/GDP)$_{i,t-1}$	0.540***	0.543***	0.540***
	(0.081)	(0.084)	(0.082)
Δ(Household credit/GDP)$_{i,t-2}$	0.049*	0.055*	0.048*
	(0.029)	(0.028)	(0.029)
ΔTop 1% share$_{i,t-1}$	0.425*	3.707**	3.452***
	(0.226)	(1.515)	(1.281)
ΔTop 1% share$_{i,t-2}$	0.451**	−1.926	−1.954
	(0.228)	(1.690)	(1.436)
LTO$_i$ × ΔTop 1% share$_{i,t-1}$	−0.013***		−0.012***
	(0.004)		(0.004)
LTO$_i$ × ΔTop 1% share$_{i,t-2}$	−0.007*		−0.007*
	(0.004)		(0.004)
Health care cov.$_{i,t-1}$ × ΔTop 1% share$_{i,t-1}$		−0.040**	−0.031**
		(0.015)	(0.013)
Health care cov.$_{i,t-2}$ × ΔTop 1% share$_{i,t-2}$		0.020	0.024
		(0.017)	(0.016)
Creditor rights$_{i,t-1}$ × ΔTop 1% share$_{i,t-1}$	0.191**	0.115	0.221**
	(0.094)	(0.101)	(0.087)
Creditor rights$_{i,t-2}$ × ΔTop 1% share$_{i,t-2}$	0.096	−0.0003	0.066
	(0.095)	(0.097)	(0.092)
Creditor rights$_{i,t-1}$	1.133***	1.165***	1.130***
	(0.426)	(0.441)	(0.424)
Creditor rights$_{i,t-2}$	−0.983**	−1.018**	−0.983**
	(0.449)	(0.449)	(0.443)
ΔReal GDP per capita$_{i,t-1}$	0.972***	0.902***	0.917***
	(0.359)	(0.348)	(0.341)
ΔReal GDP per capita$_{i,t-2}$	0.688	0.814*	0.739
	(0.491)	(0.479)	(0.484)
Δ(Current account/GDP)$_{i,t-1}$	0.056	0.073	0.058
	(0.056)	(0.058)	(0.056)
Δ(Current account/GDP)$_{i,t-2}$	0.039	0.026	0.035
	(0.043)	(0.047)	(0.043)
Δ(Broad money/GDP)$_{i,t-1}$	−0.023	−0.023	−0.020
	(0.041)	(0.040)	(0.040)
Δ(Broad money/GDP)$_{i,t-2}$	0.012	0.003	0.010
	(0.019)	(0.019)	(0.018)
ΔReal short term interest rate$_{i,t-1}$	−0.012	−0.009	−0.011
	(0.029)	(0.029)	(0.028)
ΔReal short term interest rate$_{i,t-2}$	−0.038	−0.040	−0.039
	(0.043)	(0.042)	(0.043)
Time and country fixed effects	Yes	Yes	Yes
Number of countries	16	16	16
Observations	523	523	523
Adjusted R^2	0.412	0.406	0.412

Note: The dependent variable is the annual change in household credit-to-GDP. Robust standard errors are reported in parentheses. *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.

Table A4. Regression Results with Culture Proxies Based on the World Values Survey

	Dependent variable: Δ(Household credit/GDP)$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Δ(Household credit/GDP)$_{i,t-1}$		0.557^{***}		0.579^{***}	0.567^{***}
		(0.078)		(0.083)	(0.082)
Δ(Household credit/GDP)$_{i,t-2}$		0.036		0.039^{*}	0.041^{*}
		(0.022)		(0.022)	(0.024)
ΔTop 1% share$_{i,t-1}$	0.850^{**}	0.878^{***}	2.512	4.272	-3.554
	(0.380)	(0.316)	(4.195)	(4.201)	(3.573)
ΔTop 1% share$_{i,t-2}$	0.947^{***}	0.624^{**}	6.354^{**}	6.711^{***}	6.821^{***}
	(0.330)	(0.288)	(2.477)	(1.407)	(2.635)
Anti-nationalism$_i$ × ΔTop 1% share$_{i,t-1}$	-0.020^{***}	-0.020^{***}			-0.027^{***}
	(0.006)	(0.006)			(0.006)
Anti-nationalism$_i$ × ΔTop 1% share$_{i,t-2}$	-0.017^{***}	-0.009^{*}			0.002
	(0.006)	(0.005)			(0.009)
Avoiding Risk$_i$ × ΔTop 1% share$_{i,t-1}$			-0.029	-0.047	0.051
			(0.044)	(0.045)	(0.039)
Avoiding Risk$_i$ × ΔTop 1% share$_{i,t-2}$			-0.067^{**}	-0.069^{***}	-0.072^{**}
			(0.026)	(0.015)	(0.032)
Creditor rights$_{i,t-1}$ × ΔTop 1% share$_{i,t-1}$		0.107		0.045	0.113
		(0.084)		(0.119)	(0.088)
Creditor rights$_{i,t-2}$ × ΔTop 1% share$_{i,t-2}$		0.055		0.088	0.074
		(0.089)		(0.094)	(0.109)
Creditor rights$_{i,t-1}$		0.178		0.111	0.143
		(0.147)		(0.134)	(0.139)
ΔReal GDP per capita$_{i,t-1}$		1.142^{***}		1.208^{***}	1.131^{***}
		(0.233)		(0.263)	(0.241)
Δ(Current account/GDP)$_{i,t-1}$		0.055		0.057	0.054
		(0.069)		(0.070)	(0.074)
Δ(Broad money/GDP)$_{i,t-1}$		-0.038		-0.071^{*}	-0.055
		(0.041)		(0.041)	(0.038)
ΔReal short term interest rate$_{i,t-1}$		-0.014		-0.008	-0.002
		(0.035)		(0.033)	(0.035)
Time and country fixed effects	Yes	Yes	Yes	Yes	Yes
Number of countries	14	14	13	13	13
Observations	483	483	449	449	449
Adjusted R^2	0.082	0.388	0.062	0.388	0.397

Note: This table contains estimation results of Equation 1 for our international dataset including our culture proxies based on the World Values Survey. Anti-nationalism represents the anti-nationalistic stance of a society. Avoiding risk mirrors a society's behavior towards risks and adventures. Robust standard errors are reported in parentheses. *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.

Table A5. Regression Results with Further Cultural Dimensions (Hofstede)

	Dependent variable: Δ(Household credit/GDP)$_{i,t}$		
	(1)	(2)	(3)
Δ(Household credit/GDP)$_{i,t-1}$	0.567***	0.574***	0.567***
	(0.077)	(0.075)	(0.077)
Δ(Household credit/GDP)$_{i,t-2}$	0.028	0.027	0.028
	(0.023)	(0.025)	(0.024)
ΔTop 1% share$_{i,t-1}$	1.611	2.022	3.960*
	(1.811)	(2.488)	(2.252)
ΔTop 1% share$_{i,t-2}$	3.369	1.599	3.319
	(4.930)	(3.927)	(4.536)
LTO$_i$ $\times$ ΔTop 1% share$_{i,t-1}$	−0.016**		−0.014**
	(0.007)		(0.006)
LTO$_i$ $\times$ ΔTop 1% share$_{i,t-2}$	−0.006		−0.006
	(0.010)		(0.011)
Health care cov.$_{i,t-1}$ $\times$ ΔTop 1% share$_{i,t-1}$		−0.039*	−0.028*
		(0.021)	(0.017)
Health care cov.$_{i,t-2}$ $\times$ ΔTop 1% share$_{i,t-2}$		−0.001	0.001
		(0.020)	(0.024)
Creditor rights$_{i,t-1}$ $\times$ ΔTop 1% share$_{i,t-1}$	0.250**	0.336**	0.307***
	(0.108)	(0.133)	(0.105)
Creditor rights$_{i,t-2}$ $\times$ ΔTop 1% share$_{i,t-2}$	0.075	0.088	0.068
	(0.110)	(0.130)	(0.144)
Creditor rights$_{i,t-1}$	0.158	0.142	0.156
	(0.148)	(0.152)	(0.150)
ΔReal GDP per capita$_{i,t-1}$	1.187***	1.205***	1.170***
	(0.235)	(0.229)	(0.229)
Δ(Current account/GDP)$_{i,t-1}$	0.048	0.057	0.049
	(0.062)	(0.059)	(0.062)
Δ(Broad money/GDP)$_{i,t-1}$	−0.022	−0.025	−0.021
	(0.038)	(0.037)	(0.038)
ΔReal short term interest rate$_{i,t-1}$	−0.0002	0.001	−0.0002
	(0.035)	(0.036)	(0.035)
PDI$_i$ $\times$ ΔTop 1% share$_{i,t-1}$	0.043**	0.029	0.040**
	(0.021)	(0.019)	(0.019)
PDI$_i$ $\times$ ΔTop 1% share$_{i,t-2}$	0.003	−0.002	0.004
	(0.029)	(0.026)	(0.030)
IDV$_i$ $\times$ ΔTop 1% share$_{i,t-1}$	−0.017	−0.0001	−0.018
	(0.013)	(0.010)	(0.012)
IDV$_i$ $\times$ ΔTop 1% share$_{i,t-2}$	−0.018	−0.009	−0.018
	(0.024)	(0.015)	(0.024)
MAS$_i$ $\times$ ΔTop 1% share$_{i,t-1}$	0.003	−0.009	−0.0003
	(0.004)	(0.005)	(0.003)
MAS$_i$ $\times$ ΔTop 1% share$_{i,t-2}$	0.002	−0.002	0.002
	(0.010)	(0.006)	(0.011)
IVR$_i$ $\times$ ΔTop 1% share$_{i,t-1}$	0.004	0.023	0.010
	(0.014)	(0.015)	(0.014)
IVR$_i$ $\times$ ΔTop 1% share$_{i,t-2}$	−0.012	−0.001	−0.012
	(0.034)	(0.028)	(0.036)
UAI$_i$ $\times$ ΔTop 1% share$_{i,t-1}$	−0.033**	−0.007	−0.028*
	(0.016)	(0.016)	(0.015)
UAI$_i$ $\times$ ΔTop 1% share$_{i,t-2}$	−0.022	−0.010	−0.023
	(0.044)	(0.034)	(0.046)
Time and country fixed effects	Yes	Yes	Yes
Number of countries	16	16	16
Observations	523	523	523
Adjusted R^2	0.406	0.405	0.405

Note: This table contains estimation results for our international dataset including further cultural dimensions from the Hofstede Insights database. The dependent variable is the annual change in household credit-to-GDP. The other Hofstede dimensions are power distance (PDI), individualism versus collectivism (IDV), masculinity versus femininity (MAS), indulgence versus restraint (IVR), uncertainty avoidance index (UAI). Robust standard errors are reported in parentheses. *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.

Table A6. Regression Results with Further Institutional Variables (Worldwide Governance Indicators)

	Dependent variable: Δ(Household credit/GDP)$_{i,t}$		
	(1)	(2)	(3)
Δ(Household credit/GDP)$_{i,t-1}$	0.663***	0.688***	0.673***
	(0.077)	(0.048)	(0.050)
Δ(Household credit/GDP)$_{i,t-2}$	−0.098***	−0.104***	−0.109***
	(0.023)	(0.026)	(0.027)
ΔTop 1% share$_{i,t-1}$	2.938	9.357***	8.875***
	(1.811)	(2.240)	(2.057)
ΔTop 1% share$_{i,t-2}$	−1.741	−2.484	−1.528
	(4.930)	(3.141)	(2.901)
LTO$_i$ $\times$ ΔTop 1% share$_{i,t-1}$	−0.019***		−0.015**
	(0.007)		(0.008)
LTO$_i$ $\times$ ΔTop 1% share$_{i,t-2}$	−0.008		−0.007
	(0.010)		(0.007)
Health care cov.$_{i,t-1}$ $\times$ ΔTop 1% share$_{i,t-1}$		−0.093***	−0.070***
		(0.023)	(0.023)
Health care cov.$_{i,t-2}$ $\times$ ΔTop 1% share$_{i,t-2}$		−0.006	−0.004
		(0.037)	(0.037)
Creditor rights$_{i,t-1}$ $\times$ ΔTop 1% share$_{i,t-1}$	0.546***	0.615***	0.640***
	(0.108)	(0.122)	(0.124)
Creditor rights$_{i,t-2}$ $\times$ ΔTop 1% share$_{i,t-2}$	0.258**	0.198	0.257
	(0.110)	(0.187)	(0.177)
Creditor rights$_{i,t-1}$	−0.304**	−0.315	−0.376
	(0.148)	(0.350)	(0.390)
ΔReal GDP per capita$_{i,t-1}$	0.943***	0.920*	0.904*
	(0.235)	(0.486)	(0.469)
Δ(Current account/GDP)$_{i,t-1}$	0.102	0.116	0.104
	(0.062)	(0.089)	(0.091)
Δ(Broad money/GDP)$_{i,t-1}$	−0.023	−0.025	−0.021
	(0.038)	(0.046)	(0.044)
ΔReal short term interest rate$_{i,t-1}$	0.088**	0.070	0.083
	(0.035)	(0.088)	(0.087)
PVE$_{i,t-1}$ $\times$ ΔTop 1% share$_{i,t-1}$	−0.367	−0.448	−0.285
	(0.432)	(0.490)	(0.449)
PVE$_{i,t-2}$ $\times$ ΔTop 1% share$_{i,t-2}$	−0.868**	−1.004**	−0.789*
	(0.433)	(0.418)	(0.432)
RLE$_{i,t-1}$ $\times$ ΔTop 1% share$_{i,t-1}$	−5.845***	−5.334***	−6.006***
	(1.182)	(0.994)	(1.153)
RLE$_{i,t-2}$ $\times$ ΔTop 1% share$_{i,t-2}$	−0.379	0.347	−0.129
	(1.053)	(1.182)	(1.126)
VAE$_{i,t-1}$ $\times$ ΔTop 1% share$_{i,t-1}$	−0.545	0.870	0.237
	(1.109)	(0.947)	(1.075)
VAE$_{i,t-2}$ $\times$ ΔTop 1% share$_{i,t-2}$	−0.178	0.020	−0.122
	(1.229)	(1.461)	(1.475)
GEE$_{i,t-1}$ $\times$ ΔTop 1% share$_{i,t-1}$	3.709***	3.263***	3.314***
	(0.628)	(0.878)	(0.698)
GEE$_{i,t-2}$ $\times$ ΔTop 1% share$_{i,t-2}$	2.675*	2.736*	2.668*
	(1.417)	(1.518)	(1.442)
RQE$_{i,t-1}$ $\times$ ΔTop 1% share$_{i,t-1}$	−0.104	−0.463	−0.289
	(0.362)	(0.342)	(0.318)
RQE$_{i,t-2}$ $\times$ ΔTop 1% share$_{i,t-2}$	−0.812*	−0.745	−0.793*
	(0.458)	(0.467)	(0.477)
CCE$_{i,t-1}$ $\times$ ΔTop 1% share$_{i,t-1}$	1.643	1.840	2.047*
	(1.292)	(1.199)	(1.191)
CCE$_{i,t-2}$ $\times$ ΔTop 1% share$_{i,t-2}$	0.318	−0.043	0.084
	(0.841)	(0.959)	(0.885)
Time and country fixed effects	Yes	Yes	Yes
Number of countries	16	16	16
Observations	245	245	245
Adjusted R^2	0.546	0.545	0.546

Note: This table contains estimation results for our international dataset including Worldwide Governance Indicators (WGI), which are published by the World Bank (Kaufmann et al., 2011). The dependent variable is the annual change in household credit-to-GDP. The Worldwide Governance Indicators are political stability and absence of violence/terrorism (PVE), rule of law (RLE), voice and accountability (VAE), government effectiveness (GEE), regulatory quality (RQE), control of corruption (CCE). The time period is reduced (1996 to 2016) due to data availability of WGI. Robust standard errors are reported in parentheses. *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.

Table A7. Regression Results – U.S. (Top 10% share)

	Dependent variable: Δ(Household credit/GDP)$_{i,t}$			
	(1)	(2)	(3)	(4)
Δ(Household credit/GDP)$_{i,t-1}$		0.415^{***}		0.412^{***}
		(0.074)		(0.075)
Δ(Household credit/GDP)$_{i,t-2}$		0.125^{***}		0.137^{***}
		(0.044)		(0.046)
ΔTop 10% share$_{i,t-1}$	-81.557	31.182	0.491	2.223^{**}
	(74.262)	(101.429)	(1.239)	(0.993)
ΔTop 10% share$_{i,t-2}$	161.190^{*}	127.702^{*}	3.969^{*}	3.856^{**}
	(97.932)	(69.636)	(2.112)	(1.698)
Anti-nationalism$_{i,t-1}$ $\times$ ΔTop 10% share$_{i,t-1}$	0.819	-0.314		
	(0.745)	(1.019)		
Anti-nationalism$_{i,t-2}$ $\times$ ΔTop 10% share$_{i,t-2}$	-1.620^{*}	-1.284^{*}		
	(0.984)	(0.700)		
Health care coverage$_{i,t-1}$ $\times$ ΔTop 10% share$_{i,t-1}$			-0.007	-0.026^{**}
			(0.014)	(0.012)
Health care coverage$_{i,t-2}$ $\times$ ΔTop 10% share$_{i,t-2}$			-0.047^{*}	-0.046^{**}
			(0.024)	(0.019)
ΔReal GDP per capita$_{i,t-1}$		0.883^{***}		0.904^{***}
		(0.253)		(0.253)
ΔReal wages per capita$_{i,t-1}$		1.072^{*}		1.055^{*}
		(0.615)		(0.607)
Time and state fixed effects	Yes	Yes	Yes	Yes
Observations	500	500	500	500
Number of states	50	50	50	50
Adjusted R^2	0.017	0.269	0.012	0.275

Note: This table contains estimation results of the fixed effects model for our U.S. state-level dataset. The dependent variable is the annual change in household credit-to-GDP. ΔTop 10% share is the change in the share of state income going to the Top 10% income earners. Anti-nationalism is the long-term orientation proxy, obtained by subtracting yearly non-prior service enlisted accessions to the U.S. military as a share of U.S. state population from 100. Health care coverage rate is the risk aversion proxy. Real GDP per capita and real wages per capita are stated in thousands of U.S. dollars. Robust standard errors are reported in parentheses. *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.

Table A8. Two-step System GMM - Long-termism

	Dependent variable: Δ(Household credit/GDP)$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Δ(Household credit/GDP)$_{i,t-1}$	0.372***	0.401***	0.385***	0.432***	0.477***
	(0.105)	(0.095)	(0.139)	(0.103)	(0.104)
ΔTop 1% share$_{i,t-1}$	-160.004	-182.641	-223.485	-341.000	49.453
	(157.981)	(155.018)	(148.819)	(385.673)	(80.400)
ΔTop 1% share$_{i,t-2}^{(b)}$	243.292**	222.550**	376.886***	533.504**	144.493**
	(103.087)	(100.601)	(106.867)	(256.788)	(59.209)
Anti-nat.$_{i,t-1}$ × ΔTop 1% share$_{i,t-1}$	1.608	1.837	2.241	3.429	-0.497
	(1.587)	(1.558)	(1.492)	(3.877)	(0.807)
Anti-nat.$_{i,t-2}$ × ΔTop 1% share$_{i,t-2}^{(a)}$	-2.452**	-2.241**	-3.794***	-5.363**	-1.454**
	(1.037)	(1.012)	(1.075)	(2.581)	(0.594)
ΔReal GDP per capita$_{i,t-1}^{(d)}$	0.122	0.586	0.841**	0.931***	1.336***
	(0.600)	(0.393)	(0.382)	(0.342)	(0.331)
ΔReal wages per capita$_{i,t-1}^{(c)}$	4.741**	2.769*	1.107	-0.704	-0.280
	(2.243)	(1.579)	(1.513)	(0.775)	(0.685)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Instrumental variables	a,b,c,d	a,b,c	a,b	a	-
Number of instruments	38	34	30	27	24
Hansen J-test	0.260	0.232	0.527	0.573	0.102
AR(1)	0.000	0.000	0.000	0.000	0.001
AR(2)	0.670	0.522	0.285	0.889	0.299
Observations	550	550	550	550	550
Number of states	50	50	50	50	50

Note: This table contains the results of the two-step system GMM estimator for our U.S. state-level dataset. The dependent variable is the annual change in household credit-to-GDP. ΔTop 1% share is the change in the share of state income going to the Top 1% income earners. Anti-nationalism is the long-term orientation proxy, obtained by subtracting yearly non-prior service enlisted accessions to the U.S. military as a share of U.S. state population from 100. Real GDP per capita and real wages per capita are stated in thousands of U.S. dollars. The Hansen J-test of overidentified restrictions reports p-values for the null hypothesis of instrument validity. The values reported for the Arellano-Bond test for AR(1) and AR(2) are p-values connected to the null hypothesis of no first- and second-order serial correlation in the first-differences residuals, respectively. All regressions follow Roodman (2009b) and collapse the instrument matrix to reduce the number of instruments in order to increase the reliability of the Hansen J-test. The in parentheses reported two-step robust standard errors are corrected by Windmeijer's (2005) finite-sample correction procedure, without which the standard errors would tend to be downward biased. *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.

Table A9. Two-step System GMM - Risk Aversion

	Dependent variable: Δ(Household credit/GDP)$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Δ(Household credit/GDP)$_{i,t-1}$	0.447***	0.466***	0.534***	0.517***	0.498***
	(0.102)	(0.100)	(0.121)	(0.091)	(0.122)
ΔTop 1% share$_{i,t-1}$	-3.681	-4.239	-4.458	-4.270	1.123
	(5.129)	(6.261)	(6.911)	(6.485)	(1.151)
ΔTop 1% share$_{i,t-2}{}^{(b)}$	8.665***	9.477***	11.191**	10.857*	3.678*
	(3.224)	(3.350)	(4.555)	(5.519)	(1.867)
Health care cov.$_{i,t-1}$ $\times$ ΔTop 1% share$_{i,t-1}$	0.045	0.053	0.058	0.052	-0.012
	(0.061)	(0.075)	(0.080)	(0.078)	(0.014)
Health care cov.$_{i,t-2}$ $\times$ ΔTop 1% share$_{i,t-2}{}^{(a)}$	-0.109***	-0.116***	-0.136**	-0.129*	-0.045**
	(0.040)	(0.040)	(0.056)	(0.065)	(0.022)
ΔReal GDP per capita$_{i,t-1}{}^{(d)}$	0.755	0.955*	1.320***	1.349***	1.400***
	(0.733)	(0.495)	(0.369)	(0.358)	(0.365)
ΔReal wages per capita$_{i,t-1}{}^{(c)}$	2.600	1.234	-1.064	-0.460	-0.338
	(2.987)	(2.216)	(1.312)	(0.654)	(0.781)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Instrumental variables	a,b,c,d	a,b,c	a,b	a	-
Number of instruments	38	34	30	27	24
Hansen J-test	0.155	0.317	0.409	0.618	0.113
AR(1)	0.000	0.000	0.001	0.000	0.001
AR(2)	0.414	0.348	0.272	0.440	0.189
Observations	550	550	550	550	550
Number of states	50	50	50	50	50

Note: This table contains the results of the two-step system GMM estimator for our U.S. state-level dataset. The dependent variable is the annual change in household credit-to-GDP. ΔTop 1% share is the change in the share of state income going to the Top 1% income earners. Health care coverage rate is the risk aversion proxy. Real GDP per capita and real wages per capita are stated in thousands of U.S. dollars. The Hansen J-test of overidentified restrictions reports p-values for the null hypothesis of instrument validity. The values reported for the Arellano-Bond test for AR(1) and AR(2) are p-values connected to the null hypothesis of no first- and second-order serial correlation in the first-differences residuals, respectively. All regressions follow Roodman (2009b) and collapse the instrument matrix to reduce the number of instruments in order to increase the reliability of the Hansen J-test. The in parentheses reported two-step robust standard errors are corrected by Windmeijer's (2005) finite-sample correction procedure, without which the standard errors would tend to be downward biased. *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.

Table A10. Summary Statistics before Propensity Score Matching

Variable	Treatment	Control	Treatment-Control	p-value
Number of States	4	46		
Household credit/GDP	78.927	87.073	-8.146	0.316
Top 1% share	17.505	17.142	0.363	0.915
Anti-nationalism	99.325	99.391	-0.066	0.193
Health care coverage rate	83.938	87.030	-3.092	0.108
Real GDP per capita	38.413	45.982	-7.569	0.087
Real wage per capita	16.288	20.231	-3.944	0.019
Unemployment rate	5.6	5.139	0.461	0.288
Minimum wage	5.15	5.537	-0.387	0.001

Note: This table shows summary statistics for the main variables of interest to our U.S. state-level regression analysis in 2004 – the year of the income inequality shock caused by Hurricane Katrina. The states in the treatment group are Alabama, Florida, Louisiana, and Mississippi.

Table A11. Summary Statistics after Propensity Score Matching

Variable	Treatment	Control	Treatment-Control	p-value
Number of States	4	4		
Household credit/GDP	78.927	84.987	-6.061	0.649
Top 1% share	17.505	15.273	2.233	0.544
Anti-nationalism	99.325	99.362	-0.037	0.511
Health care coverage rate	83.938	83.708	0.230	0.902
Real GDP per capita	38.413	38.237	0.177	0.963
Real wage per capita	16.288	16.289	-0.001	0.999
Unemployment rate	5.6	5.3	0.3	0.463
Minimum wage	5.15	5.15	0	NA

Note: This table shows summary statistics for the main variables of interest to our U.S. state-level regression analysis in 2004 – the year of the income inequality shock caused by Hurricane Katrina. We perform propensity score matching based on anti-nationalism, the health care coverage rate, real GDP per capita, real wage per capita, the unemployment rate, and the minimum wage in the year 2004. The states in the treatment group are Alabama, Florida, Louisiana, and Mississippi. The states in the control group are Arizona, Kentucky, New Mexico, and West Virginia.

Table A12. Difference-in-Difference Regression Results – Hurricane Katrina (after Propensity Score Matching)

	Dependent variable:			
	ΔTop 1% share$_{i,t}$ (2004–2005)		Δ(Household credit/GDP)$_{i,t}$ (2005–2006)	
	(1)	(2)	(3)	(4)
Constant	1.599***	1.911***	1.475	−9.101***
	(0.558)	(0.372)	(1.154)	(1.598)
Treat$_i$	0.152	−1.024	−7.587*	−6.780**
	(1.361)	(0.690)	(4.283)	(2.789)
Post$_t$	0.405	−4.028***	4.218	7.118***
	(0.310)	(1.147)	(2.859)	(1.457)
Treat$_i$ × Post$_t$	1.248	3.706***	11.022***	9.973***
	(0.880)	(0.969)	(4.155)	(2.793)
ΔReal GDP per capita$_{i,t-1}$		−0.257		0.758
		(0.387)		(0.863)
ΔReal wages per capita$_{i,t-1}$		7.099***		36.956***
		(1.471)		(7.887)
ΔUnemployment$_{i,t-1}$		−2.942***		4.231***
		(1.127)		(1.288)
Number of states	8	8	8	8
Observations	16	16	16	16
Adjusted R^2	0.060	0.136	0.260	0.322

Note: This table contains estimation results of Equations 2 and 3 for our quasi-natural experiment after performing propensity score matching. The dependent variable is the change in the Top 1% income share in the first and second column. In the third and fourth column, the dependent variable is the annual change in household credit-to-GDP. The year of the income inequality shock is 2004. The shock to household credit is lagged by one year. The treatment group is composed of Alabama, Florida, Louisiana, and Mississippi. The control group consists of Arizona, Kentucky, New Mexico, and West Virginia. Real GDP per capita and real wages per capita are stated in thousands of U.S. dollars. ΔUnemployment is the change in the state's unemployment rate in percentage points. ΔMinimum wage is the change in the state's minimum wage in U.S. dollars. Robust standard errors are reported in parentheses. *, ** and *** denote the statistical significance at the 10%, 5% and 1% level, respectively.