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INCOME DISTRIBUTION AND AGGREGATE SAVING: A NON-MONOTONIC RELATIONSHIP

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Drawing on a panel of advanced economies, this paper documents a concave and non-monotonic link between inequality and the aggregate household saving rate. We find that, at a low level of inequality, more inequality is associated with higher saving; but we also show that a negative relationship between inequality and saving prevails where inequality is high. Using different empirical approaches, we locate the turning point, where the marginal effect of inequality turns from positive to negative, at a net income Gini coefficient of around 30. Moreover, we show that the relationship between inequality and saving also depends on financial market conditions. While inequality increases saving, when credit is scarce it tends to reduce saving at high levels of credit. This paper primarily focuses on household saving, yet we also find some evidence for a non-monotonic effect of inequality on private saving, national saving, and the current account balance.

JEL Codes: C23, D31, E21, O5

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1. INTRODUCTION

Is there an empirical link between income distribution and aggregate saving? This paper suggests *yes*, but in a non-monotonic way. It suggests that at a low level of inequality, more inequality is associated with higher saving, but it also shows that a negative relationship between inequality and saving prevails at high levels of inequality.

Given the secular rise in income inequality, economists increasingly focus on the macroeconomic implications of this development. A link between inequality and saving lies at the heart of this literature. For instance, the debate about secular stagnation has drawn new attention to the Keynesian idea that rising inequality increases the aggregate propensity to save and thus exerts a drag on aggregate demand (e.g. Eggertsson and Mehrotra, 2014; Summers, 2015). Assuming the same positive relationship between inequality and saving, but coming to a different conclusion, the neoclassical growth literature suggests that inequality promotes economic performance by fostering capital accumulation (Bourguignon, 1981).

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Yet, with regard to global current account imbalances, some studies argue that an increase in inequality lowers private saving and the current account (Al-Hussami and Remesal, 2012; Ranciere *et al*., 2012; Behringer and van Treeck, 2013).

Although household saving constitutes a common transmission variable in all these strands of literature, the link between income inequality and saving is theoretically and empirically unclear. As richer households tend to have a higher propensity to save than households at the lower end of the income distribution (e.g. Dynan *et al*., 2004), an increase in income inequality may cause a rise in aggregate saving (Keynes 1936, 1939). Yet, if households engage in upward-looking interpersonal comparison, middle- and low-income earners might lower their saving rate in response to rising top incomes (Drechsel-Grau and Schmid, 2014; Bertrand and Morse, 2016). Thus an increase in inequality could just as well trigger expenditure cascades and a decline in aggregate saving (Alvarez-Cuadrado and El-Attar Vilalta 2012; Frank *et al*. 2014).

In line with the theoretical ambiguity, cross-country and panel-data studies that investigate the effect of inequality on national or private saving rates often remain inconclusive (Schmidt-Hebbel and Servén, 2000; Li and Zou, 2004; Leigh and Posso, 2009). With regard to household saving, some studies find a negative effect of inequality, albeit they rely on samples of only a few countries (Leigh and Posso, 2009; Alvarez-Cuadrado and El-Attar Vilalta, 2012; Behringer and van Treeck, 2013).

The present study is the first to primarily focus on household-sector saving rates, which we prefer over national or private saving rates due to a more direct connection to the theories of interest. By combining saving rates from OECD databases with net income Gini coefficients from the Luxembourg Income Study, the paper rests on a panel of highly consistent data. Moreover, the Standardized World Income Inequality Database was used to generate a large alternative sample, with 792 observations from 29 advanced economies.

Consistent with the theoretical ambiguity and the inconclusiveness of the empirical literature, we do not find a clear linear correlation between inequality and saving. However, we reveal a highly significant hump-shaped relation between inequality and saving that is robust to a large set of controls, including equity and house prices, credit availability, and financial liberalization. We find that the impact of inequality on saving is positive at low levels of inequality, whereas it becomes negative after some turning point, which is located at a Gini coefficient of between 28 and 32. This hump-shaped pattern is robust to different data sources, estimation techniques, measures of inequality, and sample compositions.

As the availability of credit financing might be a precondition for expenditure cascades (see, e.g., Rajan, 2010; Frank *et al*., 2014; Bertrand and Morse, 2016) we also test whether the impact of inequality interacts with credit availability and financial market liberalization. We find that rising inequality tends to reduce saving if financial markets are widely liberalized or the ratio of credit to GDP is high. Nonetheless, in both a low-credit and high-credit environment, the hump-shaped relationship between inequality and saving prevails.

While we primarily focus on household saving rates, we find some evidence that the hump-shaped effect of inequality also appears for private saving rates, national saving rates, and the current account balance.

The paper proceeds as follows. Section 2 describes the theoretical background to the analysis. Section 3 briefly reviews the recent empirical literature on the household, state, and cross-country level. Section 4 describes the data, focusing on measures of saving and income distribution. Section 5 reports our baseline regression results, followed by an extensive sensitivity analysis, an exploration of interaction effects, and regressions for alternative dependent variables. Section 6 discusses the results and concludes.

2. The Theoretical Link Between Income Distribution and Household Saving

The link between income distribution and aggregate household saving is ambiguous, as there are various opposing effects on the microeconomic level, which might be offsetting in the macroeconomic aggregate. First, according to Keynes (1939), the individual propensity to consume decreases with personal income, which implies "[...] that the collective propensity for a community as a whole may depend (*inter alia*) on the distribution of incomes within it." Possible explanations for higher saving rates of richer households are bequests or wealth that enter the utility function as luxury goods (e.g. Carroll 1998). Moreover, asset-based means testing for social security benefits (e.g. Hubbard *et al*., 1995; Gruber and Yelowitz, 1999) and a subsistence consumption level that lies above the income of poorer households (Musgrove, 1980) can lower the saving rates of poorer households. Ray (1998), however, argues that middle-income households may have even higher saving rates than the rich, as the middle class aspires to build wealth in order to climb the social ladder.[1]

Assuming that the relationship between individual incomes and saving rates is positive, a rising concentration of income at the top should lead to a rise in the aggregate saving rate. However, if consumption or saving decisions of different households are mutually interrelated, the opposite can be true. According to the relative income hypothesis, "[...] the frequency and strength of impulses to increase expenditure for one individual depend entirely on the ratio of his expenditures to the expenditures of those with whom he associates" (Duesenberry, 1949, p. 32). Building upon such consumption externalities, Frank *et al*. (2014) propose a formal model of "expenditure cascades." Similarly, Alvarez-Cuadrado and El-Attar Vilalta (2012) incorporate relative income considerations into an overlapping generations (OLG) model. In both models, increasing consumption of a reference group encourages additional consumption by households further down the income

[1]Ray's line of reasoning refers to developing countries in particular. It depends on the assumption that only the rich engage in conspicuous consumption, following the consumption level of richer people in developed economies.

ranking. On aggregate, a mean preserving spread in incomes thus leads to a decrease in the saving rate.[2]

In conclusion, the prerequisite for a decline in the aggregate saving rate due to rising inequality is that saving rates of low- and middle-income earners decline sufficiently; so that the increase in the volume of saving, resulting from the shift in income toward households with a larger propensity to save, is overcompensated. To enable this decline in saving, the initial saving rates (or the financial wealth) of low- and middle-income households have to be sufficiently large. Otherwise, if saving rates (and wealth) are already low, poorer households have to borrow to finance their excess consumption.

3. A Brief Survey of the Empirical Literature

The link between income distribution and household saving has been tested in a couple of micro- and macro-data studies. Using survey data from the United States (U.S.), a highly cited study by Dynan *et al.* (2004) finds a strong positive correlation between saving rates and household incomes. Yet, based on Canadian data, Alan *et al.* (2015) indicate that saving rates do not differ substantially across long-run income groups. Like Dynan *et al.* (2004), Alvarez-Cuadrado and El-Attar Vilalta (2012) find that saving rates increase in permanent income. Moreover, the latter study emphasizes a negative correlation between the income growth of local reference groups (or an increase in inequality) and the saving rates of poorer households. Similarly, Bertrand and Morse (2016) support the relative income hypothesis and "trickle-down consumption" by showing that middle-income households consume a larger share of their income when exposed to higher upper income and consumption levels. Based on this result, they estimate that in 2005 the aggregate personal saving rate in the U.S. might have been 1.1 to 1.3 percent higher if income growth at the top had not outpaced growth at median levels. Finally, Drechsel-Grau and Schmid (2014) show that "keeping up with the Joneses behaviour" is not limited to one side of the Atlantic. Using data from the German Socio-Economic Panel, they find that an increase in reference consumption of 1 percent leads households to raise their own consumption by about 0.3 percent.

Altogether, the micro-data evidence supports both the Keynesian and the relative income hypothesis. Yet it says little about aggregate saving, because it cannot tell which of the opposing effects prevails. Therefore we have to refer to macro-data studies, which regress aggregate saving rates on aggregate measures of income distribution.

[2]A decline in the aggregate saving rate can also result from a decline or stagnation of income at the bottom of the distribution. According to the habit persistence theory (Brown, 1952), people lower their saving rate to hold on to their usual consumption level when real income deteriorates. If people are used to steady improvements in living standards, habit persistence may thus implicate lower saving when income growth slows down for certain income groups. Similarly, a decrease in aggregate saving can result when more and more households are falling below a subsistence consumption level. The latter would be most pronounced if the subsistence level was a socially acceptable consumption standard that was high enough to affect a large number of households.

In general, cross-country studies on inequality and saving often remain inconclusive and the results vary with the estimation technique and sample composition. Because of data restrictions, either national or private saving rates serve as the (main) dependent variable in most macro-data studies. To provide a better comparability within the literature and to our own paper, we restrain our survey to panel regressions and subsamples of data from developed economies or OECD members. Drawing on this selection, Schmidt-Hebbel and Servén (2000) and Li and Zou (2004), as well as Leigh and Posso (2009), do not find a consistent relationship between inequality and saving. Smith (2001), however, reports a positive effect of inequality on private saving.

To our knowledge, there are only three studies that (also) examine the effect of income distribution on the saving rate of the household sector. Regressing household saving on lagged top-income shares, in a panel of ten developed economies observed between 1975 and 2002, Leigh and Posso (2009) find no significant effect of inequality. In contrast, Alvarez-Cuadrado and El-Attar Vilalta (2012) suggest a negative impact of inequality on aggregate saving. Drawing on a sample of six developed economies, observed between 1954 and 2007, they find a negative effect of the top 5 percent income share, which is highly significant under a range of different econometric specifications. A recent study by Behringer and van Treeck (2013) primarily deals with the effect of income distribution on the current account. Yet it also takes a look at saving rates and financial balances of the household sector. In a sample of G7 economies, the study finds a significant negative effect of the top 5 percent income share, while the Gini coefficient appears to be insignificant.

Altogether, the literature on the relationship between inequality and saving remains inconclusive, which might be due to some deficiencies. First, there are only a few studies that examine the aggregate saving rate of the household sector. Second, the studies that focus on household saving are based on very few countries. Third, the existing literature does not control for a number of covariates, such as wealth effects, that could lead to an omitted variable bias. Fourth, the literature does not account for a non-monotonic relationship.

4. Data Description

4.1. *Saving Rates and Sample Composition*

Most existing studies focus on national saving, which measures the total amount of saving in the economy, including households, firms, and the government. Yet, since most theories about saving and inequality refer to household behavior, we prefer to focus on household saving rates, while we will glance at broader measures of saving and the current account balance at the end of this paper.

Although household saving rates are less readily available than national saving rates, we are able to compose a fairly large sample by combining data from the OECD National Accounts Database with data from the OECD Economic Outlook. To benefit from a homogeneous sample of high-quality data, we limit our panel to high-income OECD countries, as defined by the World Bank classification. The OECD calculates saving by subtracting household consumption expenditures from household disposable income, net of fixed-capital depreciation. Capital holding gains are not included, which is conducive to our focus on active saving behavior. Division of the saving volume by the disposable income of the household sector yields the saving rate.[3]

4.2. *Inequality Data*

The use of the correct inequality dataset for cross-national research is controversial (see Atkinson and Brandolini, 2001; Jenkins, 2015; Solt, 2015). So far, the tradeoff between a larger size of the dataset and a greater comparability among observations has not been entirely resolved. Hence, we deploy two different datasets in order to ensure the robustness of our baseline results. To provide the best comparability, we use the Key Figures from the Luxembourg Income Study (LIS), which are calculated from harmonized micro-data. In addition, we also deploy the Standardized World Income Inequality Database (SWIID), which is a secondary-source dataset that maximizes the coverage of countries and years. In any case, our primary measure of inequality is the Gini coefficient of household income after taxes and transfers.

The LIS Key Figures are widely regarded as the most consistent inequality measures (see Ravallion, 2015; Solt, 2015). Yet their coverage is very limited, restricting our regression sample to only 143 observations from 25 countries. While the selection of countries is in line with our focus on advanced economies, the time dimension is very short and obstructive to many robustness tests; for example, for differing sample compositions and alternative estimators.

Thus we also deploy version 5.0 of the Standardized World Income Inequality Database (Solt, 2009, 2016) as an alternative. The SWIID aims to provide the most comparable data for the broadest possible sample of countries and years by collecting Ginis from a large number of sources, such as cross-national inequality databases, national statistical offices, and scholarly articles. Market and net Ginis from the LIS are added as a benchmark of most reliable data. As the Ginis from the source data are often not directly comparable due to different income definitions or accounting units, the SWIID uses a multiple-imputation algorithm to estimate standardized net and market Ginis for all country–years that are not yet covered in the LIS. To reflect the uncertainty associated with these estimates, the SWIID reports 100 imputations for each observation, generated via Monte Carlo simulations.

There are two alternative paths to employ the SWIID data in regression analysis. The first is to average the imputations and to use the resulting point estimates with usual regression techniques, thereby simply ignoring the uncertainty in the inequality data. The second, which is recommended by the author of the SWIID, is to deploy multiple-imputation tools that explicitly account for data uncertainty within the estimation results. As the uncertainty related to Ginis from high-income OECD countries is relatively low, this paper primarily uses point estimates of the SWIID data. However, we also employ multiple-imputation estimation techniques to test for the robustness of our results.

[3]Notably, the household sector includes unincorporated enterprises and in most cases also non-profit institutions serving households.

A recent paper by Jenkins (2015) criticizes the comparability and quality of the data in the SWIID. However, Solt (2015) shows that most of this criticism does not apply to the current version of the database. In general, the construction and use of secondary datasets comes with some pitfalls, which are described in a seminal paper by Atkinson and Brandolini (2001). Yet Solt (2015, 2016) convincingly shows that the SWIID incorporates advice from Atkinson and Brandolini (2001, 2009) and thus poses the best choice among inequality datasets that cover many countries and years.

4.3. *Control Variables*

To isolate the true impact of income distribution on saving, we control for a number of variables that have so far been neglected in the literature on inequality and saving. First, we are concerned about wealth effects being a cause of spurious regressions. Rising asset prices may cause a drop in saving, as people feel wealthier and are able to borrow against higher collateral (e.g. Slacalek, 2009; Hüfner and Koske, 2010). However, if an asset bubble is associated with growing income inequality, these wealth effects may misleadingly be attributed to income distribution. To avoid such an omitted variable bias, we employ an indicator of real house price developments (*houses*) and real stock market returns (*equities*).

Another potentially important control is the availability of credit, which we proxy with the ratio of private credit to GDP (*credit*). Whereas financial liberalization may enhance saving opportunities, a greater availability of credit could also boost private consumption by relaxing borrowing constraints (e.g. Bandiera *et al.*, 2000). As an expanding financial sector may affect income distribution (e.g. Delis *et al.*, 2014; Bumann and Lensink, 2016), omitting financial depth may cause a bias in the estimated effect of inequality.

The remaining control variables are common in the literature on inequality and saving. The old-age dependency ratio (*depend*) is defined as the share of population aged 65 or older over the working-age population. According to the life-cycle hypothesis (Modigliani 1970), we expect a negative sign for its estimated coefficient. The variable *incgrow* denotes the growth rate of households' real disposable income per capita.[4] Because of habit persistence, an increase in income may lead to an increase in saving. However, if households are forward looking, consumption may also rise in anticipation of rising future incomes. Real interest rates are measured by the real return on long-term government bonds (*interest*). Although in standard macroeconomic models a higher interest rate increases the attractiveness of saving compared to consumption, the sign of its effect is ambiguous. If households pursue a fixed amount of savings, higher interest rates could also reduce saving, because less money needs to be put aside to reach a saving target. Further controls are the fiscal balance (*fiscal*), to account for Ricardian equivalence; the natural logarithm of GDP per capita (ln(*gdppc*)); and the inflation rate (*infl*). A more detailed description of the sources and derivations of our variables can be found in the Appendix (in the Online Supporting Information). Table 1 contains the summary statistics.

[4]We prefer the growth rate of household disposable income over the GDP growth rate, due to less severe concerns about reverse causality and its more direct impact on the household sector.

TABLE 1
Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
$saving_{hh}$	7.930	5.989	−9.043	25.776	792
$gini_{LIS}$	28.328	4.123	19.7	37.1	142
$gini_{SWIID}$	28.282	4.403	17.964	48.74	792
atk	0.142	0.04	0.073	0.235	142
S80/S20	5.167	1.684	3.057	13.414	151
P90/P10	3.668	0.794	2.43	5.732	142
P90/P50	1.825	0.176	1.505	2.231	142
top1inc	8.01	2.679	3.97	18.33	427
depend	20.888	4.732	6.433	36.018	792
incgrow	2.391	2.958	−11.046	15.995	792
interest	3.045	2.935	−14.992	20.998	792
fiscal	−2.397	4.593	−32.554	18.696	792
ln(*gdppc*)	10.303	0.329	8.762	11.346	766
infl	3.986	3.602	−4.48	24.54	792
equities	4.337	23.498	−47.79	105.33	749
houses	1.656	7.092	−17.241	38.831	685
credit	89.863	44.031	20.84	227.753	757
finreform	75.086	23.418	9.524	100	527
$saving_{prvt}$	7.875	4.047	−4.215	23.285	527
$saving_{net}$	7.996	5.783	−12.653	31.164	713
$saving_{gross}$	24.272	5.408	6.118	41.745	723
Current account	−0.145	4.639	−14.575	16.232	766

Finally, the saving rate of private households is likely to be affected by factors that are unobservable or difficult to measure. For instance, cultural attitudes (such as the proneness to competitive thinking) could be a source of omitted variable bias, if they affect attitudes toward consumption as well as the political stance toward redistribution.[5] To control for such time-invariant factors, our baseline model includes country fixed effects.

5. Empirical Findings

We now turn to the empirical assessment of the relationship between inequality and household saving. First, we present our regression model along with our baseline results. Next, we show that the results are robust to data uncertainty, endogeneity, alternative inequality measures, different sample compositions, and a flexible functional form. Then, we test whether the relationship between inequality and saving interacts with financial market conditions. Finally, we analyze the effect of inequality on some broader measures of saving as well as the current account balance.

[5]Catte and Boissinot (2005) emphasize further factors that could explain differences in household saving rates. These include the number of unincorporated enterprises in the household sector, the provision of public goods, the role of direct versus indirect taxation, and the design of the pension system. However, after adjusting the data for differences in public provision and the tax system, Catte and Boissinot (2005) find only modest effects on the level and international differences in saving rates.

5.1. *Baseline Results: A Hump-Shaped Relationship*

Tables 2 and 3 present the results of our baseline regressions, using either the LIS or the SWIID dataset. The baseline estimation equation is as follows:

$$saving_{it} = \alpha + \beta_1 gini_{it} + \beta_2 gini_{it}^2 + \beta' X_{it} + \alpha_i + (\lambda_t) + \epsilon_{it}, \tag{1}$$

where $saving_{\mathrm{it}}$ is the aggregate saving rate of the household sector in country i and year t.[6] Among the regressors, we focus on the Gini of net incomes, which we include in a linear and a squared form, to allow for a non-linear relationship. The vector X_{it} denotes our set of control variables; α_i are country fixed effects; and ε_{it} stands for the error terms. The standard errors are adjusted for the presence of arbitrary heteroskedasticity and autocorrelation.[7] Time fixed effects λ_t are introduced whenever the degrees of freedom would not become very small.

The use of inequality data from the LIS limits our regression sample to a maximum of 143 observations from 25 countries. The panel is highly unbalanced, with the earliest observation being from 1961 and the latest from 2013. Table 2 presents the estimation results. Each pair of columns reports two identical models, which only differ by the inclusion of the quadratic term of the Gini in the even numbered columns. Columns (1) and (2) report pooled OLS estimates, whereas columns (3)–(6) contain results from fixed effects regressions. We exploit the maximum number of available observations by focusing on small models in columns (1)–(4). To correct for a possible downward bias in the estimated effect of inequality, we add two measures of asset price movements (*equities* and *houses*) and the credit-to-GDP ratio (*credit*) in columns (5) and (6). Following preceding studies, we additionally include the log of real income per capita (ln(*gdppc*)) and the inflation rate (*infl*).

In line with earlier studies, Table 2 does not show a clear linear relationship between income inequality and household saving. When the standard set of control variables is applied, the effect of inequality is very small and far from significant. Yet, after the inclusion of the additional controls, the estimated effect of inequality becomes positive at the 10 percent level.

Above all, however, the estimated coefficients of *gini* and $gini^2$ in columns (2), (4), and (6) indicate a hump-shaped function between inequality and saving, which prevails with both sets of control variables. To assess the statistical significance of the non-linear relationship, the even-numbered columns report the results of the Sasabuchi–Lind–Mehlum (SLM) test, together with the slopes at the minimum

[6]We use cluster robust standard errors, which were developed by Wooldridge (2002), Williams (2000), Rogers (1994), and Froot (1989). As this methodology was developed for panels with a reasonably large cross-section relative to the time dimension, cluster robust estimates should be reliable for the LIS regression sample. Yet the time dimension is about equal to the cross-sectional dimension in the SWIID regression sample. Thus we also estimated alternative regressions with Driscoll–Kraay standard errors, which are consistent for autocorrelation and cross-sectional dependence, but have been developed for large-T asymptotics. The results are very similar and can be provided upon request.

[7]Some previous studies consolidate the annual data into 5-year averages, to deal with gaps in the data and to weaken serial correlation in the residual. Our regression results are very similar with averaged data (available upon request). Yet we prefer the use of annual data, as most of the benefits of averaging are obsolete with our dataset and the use of cluster robust standard errors.

TABLE 2
Baseline Regression Models Using Ginis from the LIS

	(1) POLS	(2) POLS	(3) FE	(4) FE	(5) FE	(6) FE
gini	−0.0109	3.870**	0.0528	3.310**	0.277*	3.473***
	(0.188)	(1.406)	(0.223)	(1.236)	(0.160)	(0.899)
$gini^2$		−0.0675***		−0.0574**		−0.0550***
		(0.0231)		(0.0216)		(0.0153)
depend	−0.0314	0.000483	−0.672**	−0.627**	−0.765**	−0.753**
	(0.163)	(0.168)	(0.240)	(0.225)	(0.354)	(0.316)
incgrow	0.188	0.214	0.339***	0.344***	0.273**	0.288**
	(0.165)	(0.166)	(0.0924)	(0.0835)	(0.119)	(0.108)
interest	0.310	0.380	−0.178	−0.115	−0.366*	−0.279
	(0.328)	(0.343)	(0.118)	(0.124)	(0.199)	(0.205)
fiscal	−0.384***	−0.381***	−0.430***	−0.440***	−0.532***	−0.526***
	(0.114)	(0.117)	(0.0644)	(0.0600)	(0.0798)	(0.0875)
ln(*gdppc*)					−0.983	−2.009
					(6.508)	(5.004)
infl					0.214	0.225
					(0.290)	(0.232)
equities					−0.00999	−0.00766
					(0.0169)	(0.0148)
houses					0.0380	0.0234
					(0.0422)	(0.0476)
credit					−0.0133	−0.00276
					(0.0200)	(0.0173)
Observations	143	143	143	143	108	108
Countries	25	25	25	25	24	24
R^2	0.148	0.194	0.428	0.476	0.568	0.610
Turning point		28.67		28.83		31.55
CI 90%		[24.90; 30.79]		[25.73; 32.63]		[28.76; 35.97]
Slope: $gini_{min}$		1.17**		1.01***		1.27***
Slope: $gini_{max}$		−1.25***		−1.05**		−0.71**
SLM *p*-value		0.014		0.014		0.024

Notes: The table reports pooled OLS (POLS) and fixed effects (FE) regressions. The dependent variable is the saving rate of the household sector. Cluster robust standard errors are reported in parentheses. The bottom part of the table reports the turning points of the inequality effect and the results of the Sasabuchi–Lind–Mehlum (SLM) test for a hump-shaped relationship. CI 90% denotes the 90 percent Fieller confidence intervals for the turning point. To ease comparison, slopes at $gini_{min}$ and $gini_{max}$ are uniformly measured at the bounds of the maximum sample of 143 observations; that is, at Ginis of 20 and 38. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 3
Baseline Regression Models Using Ginis from the SWIID

	(1) POLS	(2) POLS	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE	(8) FE
gini	−0.117	1.427	−0.0373	2.386***	0.138	3.218***	0.0513	3.159***
	(0.168)	(1.079)	(0.195)	(0.659)	(0.204)	(0.635)	(0.160)	(0.711)
gini^2		−0.0263		−0.0426***		−0.0533***		−0.0537***
		(0.0182)		(0.0130)		(0.0107)		(0.0119)
depend	−0.325**	−0.309**	−0.671***	−0.677***	−0.676***	−0.715***	−0.849***	−0.882***
	(0.143)	(0.140)	(0.118)	(0.128)	(0.188)	(0.156)	(0.203)	(0.152)
incgrow	0.448***	0.468***	0.271***	0.274***	0.385***	0.382***	0.426***	0.417***
	(0.101)	(0.107)	(0.0582)	(0.0611)	(0.0680)	(0.0642)	(0.0583)	(0.0494)
interest	−0.192	−0.175	−0.100	−0.0965	−0.130	−0.103	0.0306	−0.0215
	(0.158)	(0.157)	(0.108)	(0.112)	(0.176)	(0.156)	(0.191)	(0.159)
fiscal	−0.475***	−0.463***	−0.416***	−0.436***	−0.422***	−0.433***	−0.349**	−0.363***
	(0.155)	(0.155)	(0.103)	(0.0964)	(0.111)	(0.0959)	(0.127)	(0.111)
ln(*gdppc*)					−0.346	−1.114	−5.421	−7.502
					(4.933)	(4.035)	(8.714)	(7.654)
infl					0.0588	0.0887	0.196	0.201
					(0.162)	(0.104)	(0.220)	(0.168)
equities					−0.0155**	−0.0134**	−0.0151	−0.0163
					(0.00663)	(0.00513)	(0.0118)	(0.00994)
houses					−0.0758***	−0.0714**	−0.0539**	−0.0450*
					(0.0262)	(0.0271)	(0.0226)	(0.0236)
credit					−0.0249	−0.0152	−0.0370	−0.0252
					(0.0215)	(0.0181)	(0.0232)	(0.0202)
Year dummies	No	No	No	No	No	No	Yes	Yes
Observations	792	792	792	792	616	616	616	616
Countries	29	29	29	29	27	27	27	27
R^2	0.223	0.239	0.433	0.458	0.549	0.583	0.573	0.608
Turning point		27.09		27.97		30.20		29.40
CI 90%				[25.04; 33.23]		[26.91; 34.02]		[26.59; 32.32]
Slope: $gini_{\text{min}}$		0.48		0.85***		1.30***		1.23***
Slope: $gini_{\text{max}}$		−1.15*		−1.79***		−2.00***		−2.11***
SLM *p*-value		0.14		0.005		0.0002		0.0003

Notes: The table reports pooled OLS (POLS) and fixed effects (FE) regressions. The dependent variable is the saving rate of the household sector. Cluster robust standard errors are reported in parentheses. The bottom part of the table reports the turning points of the inequality effect and the results of the Sasabuchi–Lind–Mehlum (SLM) test for a hump-shaped relationship. CI 90% denotes the 90 percent Fieller confidence intervals for the turning point. To ease comparison, slopes at $gini_{\text{min}}$ and $gini_{\text{max}}$ are uniformly measured at the bounds of the maximum sample of 792 observations; that is, at Ginis of 18 and 49. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

and maximum values of the Gini in our sample.[8] In addition, we report the Fieller 90 percent confidence intervals for the turning points.

The SLM test rejects the null of a monotone or U-shaped relationship in favor of an inverted-U-shaped (concave and hump-shaped) relationship in each specification. With the smaller pooled OLS and fixed effects models in columns (2) and (4), the turning points are estimated at Ginis of 28.7 and 28.8, respectively. Thus the point at which the marginal effect of inequality becomes negative corresponds roughly to the median value of the Gini in our regression sample. In the extended model of column (6), the estimated turning point shifts toward a Gini of 31.6, indicating that the new controls may have resolved a small downward bias.[9]

The use of inequality data from the SWIID vastly expands the regression sample. Yet Table 3, which is based on a sample of up to 792 observations from 29 countries, presents very similar results with respect to the hump-shaped relationship between inequality and saving. Whereas a linear effect of inequality is never significant with the SWIID sample, the coefficients of *gini* and $gini^2$ are again highly significant in all fixed effects estimations. The positions of the turning points are also similar to the estimates from the LIS sample. In the small fixed effects model of column (4), the marginal effect of inequality turns from positive to negative at a Gini of 28. After introducing the additional controls in columns (5) and (6), the turning point shifts slightly rightwards to a Gini of 30.2. In contrast to the LIS sample, asset prices are now negatively correlated with the saving rate. In columns (7) and (8), we finally add year dummies to account for common shocks such as the Global Financial Crisis. While only few of these dummies are significant, their introduction slightly affects the estimates of the other control variables. Nonetheless, for *gini* and $gini^2$, the results remain almost unchanged, yielding a hump-shaped relationship with a turning point at a Gini of 29.4.[10]

In sum, our regression models resemble earlier studies that do not find a linear relationship between income inequality and the aggregate saving rate. However, by introducing a quadratic term, we reveal a hump-shaped relationship, which peaks at a net Gini roughly between 28 and 32.

Figure 1 illustrates the marginal effect of inequality on saving across different values of the Gini. It pictures how the effect of inequality is decreasing with an increasing level of inequality. The marginal effect of inequality ranges from 0.85 at the smallest Gini in the sample (Gini of 18, observed in Sweden in 1990) toward −1.79 at the upper bound (Gini of 49, in Chile in 2009). In line with the results from the SLM test, the confidence intervals reveal a significantly positive effect of

[8]The SLM test was developed by Lind and Mehlum (2010), based on the work of Sasabuchi (1980). To allow for comparability between different models, we report the slopes at the boundaries of the sample from column (1); that is, at Ginis of 20 and 38.

[9]In parts, the shift to the right is also caused by changes in the sample composition: when we run regression (4) on the reduced sample of 108 observations from regression (6), the turning point is estimated at a Gini of 30.

[10]Following Grigoli *et al*. (2014) and Loayza *et al*. (2000), we also added the share of urban population, terms of trade, and the young-age dependency ratio as additional regressors. Whereas the latter two variables are positively related to saving, the results for *gini* and $gini^2$ are almost unchanged by this exercise. Finally, the concave relationship is also robust to the fixed effects model from Schmidt-Hebbel and Servén (2000) who control for young- and old-age dependency, GDP growth, per capita GDP, and also the square of per capita GDP. The results are available upon request.

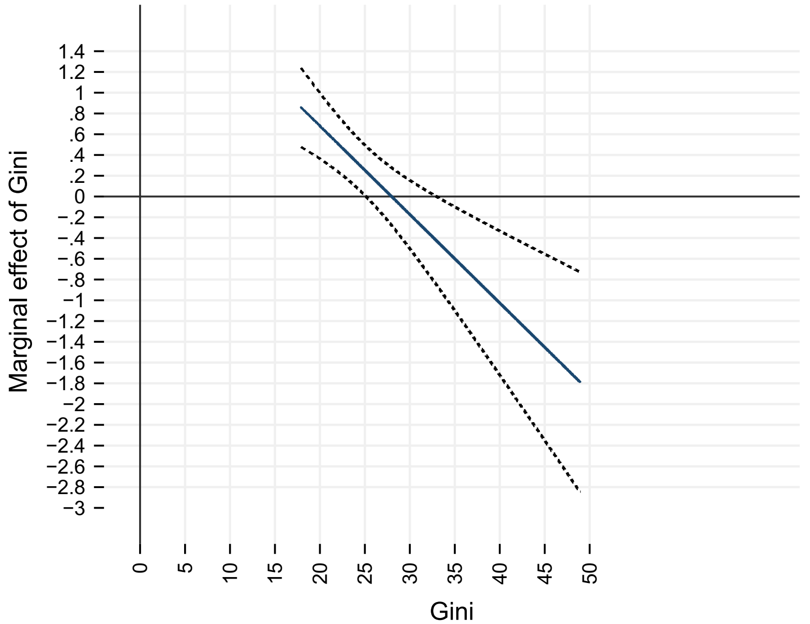

Figure 1. The Marginal Effect of Inequality on Saving at Different Levels of Inequality [Colour figure can be viewed at wileyonlinelibrary.com]

Notes: Values are calculated using the results from column (4) of Table 3. The downward-sloping line plots the marginal effect of inequality. The surrounding dotted lines represent the 90 percent confidence intervals.

inequality for Ginis ranging from 18 to 25 and a significantly negative effect for Ginis above 33.

To get an idea of the countries that have driven the non-linear effect, Figure 2 plots the Ginis observed in 1995 along with the associated marginal effects.[11] Looking at the two polar cases, the figure predicts a strong positive effect of rising inequality on saving in Sweden and a negative effect in the U.S.

5.2. *Robustness Tests*

This section analyzes the robustness of the hump-shaped relationship. As many of the following robustness tests require a comprehensive sample, we always apply inequality data from the SWIID, if not mentioned otherwise.

Multiple-Imputation Estimations

First, we test whether the uncertainty that is associated with the SWIID data affects our results. Therefore, we follow the advice from Solt (2016) and employ a multiple-imputation technique to account for data uncertainty. Essentially, the multiple-imputation estimation routine of Stata®, which we

[11]Corresponding figures for different time periods are available upon request. We report the marginal effects in 1995 as this constitutes a time period that stands rather at the beginning of the sample, but already contains most of the countries.

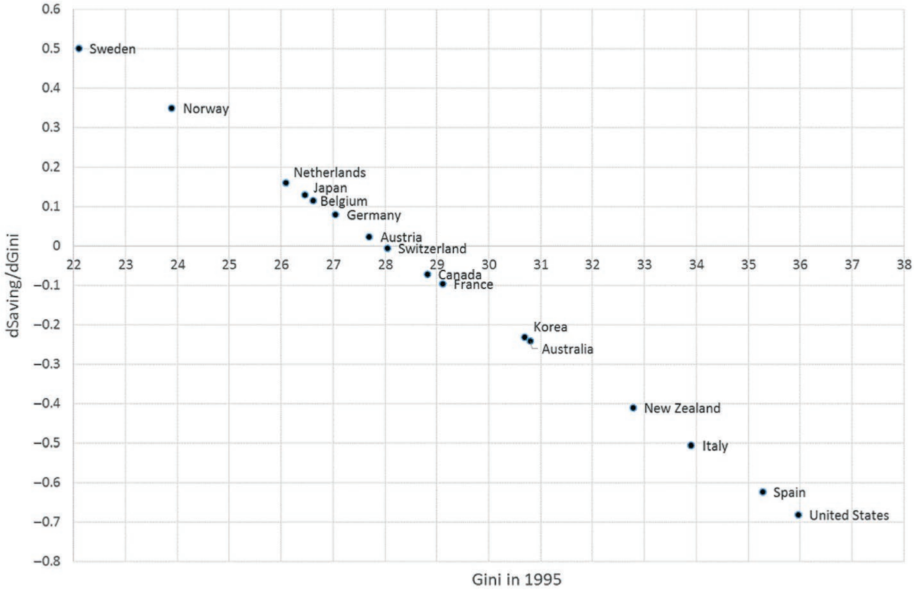

Figure 2. The Marginal Effect of Inequality on Saving at 1995 Gini Levels [Colour figure can be viewed at wileyonlinelibrary.com]

Notes: Values are calculated using the results from column (4) of Table 3.

apply in this section, runs repeated regressions for each of the 100 imputations of the net Gini and then pools the resulting estimates following the combination rules proposed by Rubin (1987). Thus the estimated coefficients and standard errors are adjusted for the variability between imputations, whereas regressions on averaged data treat the Gini from the SWIID as an error-free variable.[12]

Table 4 presents the multiple-imputation regressions. To provide direct comparability, each regression exactly resembles the quadratic models of the baseline specification, but is estimated with the multiple-imputation technique. Just as in the baseline table, we find a hump-shaped relationship between inequality and saving. The effect of inequality remains highly significant and the locations of the turning points almost unchanged, although the estimated coefficients become somewhat smaller and the standard errors slightly larger.[13]

Altogether, the enhanced statistical accuracy stemming from multiple-imputation estimations hardly affects our results, which means that we can safely proceed with less computation-intensive regression techniques.

[12]Brownstone and Valletta (2001) offer an excellent summary of the multiple estimation technique and its applications in economics.

[13]The resulting slightly decreased standard errors together with flattened regression lines are surprising, given that we would normally expect that multiple-imputation estimations increase the standard errors. We are grateful to Frederic Solt for pointing out a possible explanation: in cases where influential outliers with large standard errors are pulling up the coefficients, the use of multiple imputations may flatten the coefficients and also estimate them with more precision.

TABLE 4
Multiple-Imputation Estimates

	(1) POLS	(2) FE	(3) FE	(4) FE
$gini_{mi}$	1.388	2.179***	2.939***	2.917***
	(1.042)	(0.665)	(0.646)	(0.696)
$gini^2_{mi}$	−0.0256	−0.0389***	−0.0487***	−0.0496***
	(0.0176)	(0.0130)	(0.0112)	(0.0119)
depend	−0.310**	−0.683***	−0.712***	−0.883***
	(0.140)	(0.126)	(0.159)	(0.156)
incgrow	0.468***	0.274***	0.384***	0.419***
	(0.108)	(0.0612)	(0.0657)	(0.0504)
interest	−0.176	−0.0975	−0.108	−0.0173
	(0.157)	(0.112)	(0.156)	(0.161)
fiscal	−0.463***	−0.435***	−0.431***	−0.361***
	(0.155)	(0.0972)	(0.0983)	(0.113)
ln(*gdppc*)			−1.059	−7.421
			(4.105)	(7.754)
infl			0.0829	0.201
			(0.109)	(0.171)
equities			−0.0136**	−0.0161
			(0.00526)	(0.0101)
houses			−0.0726**	−0.0459*
			(0.0279)	(0.0238)
credit			−0.0159	−0.0261
			(0.0183)	(0.0204)
Year dummies	No	No	No	Yes
Observations	792	792	616	616
Countries	29	29	27	27
Turning point	27.06	28.07	30.19	29.4

Notes: The table presents multiple-imputation estimates of the baseline pooled OLS (POLS) and fixed effects (FE) regression models. The dependent variable is the saving rate of the household sector. Cluster robust standard errors are reported in parentheses. The final line of the table reports the turning points of the inequality effect. Ginis are sourced from the SWIID. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Addressing Endogeneity via Lag Identification, 2SLS, and System GMM

So far, we have merely assumed that we are measuring a causal effect of inequality on saving. Yet, although the case for reverse causation is not very strong, some simultaneity bias cannot be ruled out. This section applies various instrumental variable techniques to counter the potential endogeneity of inequality.[14]

In column (1) of Table 5, we follow the simplest approach for causal inferences in a panel setting by using lagged instead of contemporaneous values of the explanatory variables. The results are almost identical to those from estimations with contemporaneous regressors, confirming the hump-shaped relationship with a peak value that is roughly located at a Gini of 28. The same is true when we vary the lag length between 2 and 5 years (the results are available upon request), similarly to the approach taken by Leigh and Posso (2009).

[14]While the present paper focuses on the potential endogeneity of the Gini coefficient, it is also possible that the results are biased due to endogenous control variables. The working paper version of this article demonstrates that instrumenting potentially endogenous controls (such as income growth, interest rates, and the fiscal balance) does not alter the estimated effect of inequality.

TABLE 5
Lagged Regressors, 2SLS, and System GMM

	(1) Lag t−1 FE	(2) 2SLS FE	(3) 2SLS FE	(4) System GMM	(5) 2SLS FE	(6) 2SLS FE
$saving_{t-1}$			0.816^{***}	0.946^{***}		
			(0.0260)	(0.0344)		
gini	2.190^{***}	3.299^{***}	0.913^{***}	1.032^{**}	13.58^{***}	10.84^{***}
	(0.608)	(0.532)	(0.344)	(0.516)	(2.381)	(3.354)
$gini^2$	-0.0393^{***}	-0.0577^{***}	-0.0160^{***}	-0.0176^{*}	-0.244^{***}	-0.179^{***}
	(0.0120)	(0.0105)	(0.00554)	(0.00955)	(0.0443)	(0.0548)
depend	-0.689^{***}	-0.709^{***}	−0.0374	0.00848	-0.801^{***}	-1.045^{***}
	(0.138)	(0.127)	(0.0338)	(0.0427)	(0.162)	(0.173)
incgrow	0.252^{***}	0.269^{***}	0.404^{***}	0.136	0.329^{***}	0.283^{***}
	(0.0895)	(0.0615)	(0.0380)	(0.0998)	(0.0803)	(0.0683)
interest	−0.136	−0.0987	−0.0566	−0.0442	−0.0849	−0.0162
	(0.122)	(0.121)	(0.0360)	(0.0459)	(0.0865)	(0.0735)
fiscal	-0.326^{***}	-0.453^{***}	-0.194^{***}	−0.00852	-0.459^{***}	-0.492^{***}
	(0.0945)	(0.0937)	(0.0290)	(0.0384)	(0.0666)	(0.0661)
Instruments		$L(2/3).gini$	$L(2/3).gini$	$L(2/3)$	$avg.gini(n-i)$	$gini_{\text{Sweden}} \times proxSweden$
Observations	793	772	769	789	766	710
Countries	29	29	29	29	29	28
AR(1) p-value				0.00003		
AR(2) p-value				0.816		
Hansen J p-value		0.265	0.741	0.086	Exact. indent.	Exact. indent.
KP LM p-value		0.027	0.031	0.048/0.032	0.0007	0.0005
KP F-statistic		62.991	63.980	1.260/0.716	6.165	5.904
Turning point	27.86	28.58	28.52	29.31	27.77	30.29
SLM p-value		0.000	0.009	0.042	0.000	0.001

Notes: The dependent variable is the saving rate of the household sector. Column (1) presents a fixed effects model with regressors that are lagged for one period. Columns (2) and (3) report 2SLS (two-stage least squares) fixed effects estimations, where *gini* and $gini^2$ are instrumented by lags 2 and 3. Column (4) reports a one-step system GMM estimation with cluster robust standard errors, a collapsed instrument matrix, and orthogonal deviations. All variables except *depend* are treated as endogenous. Columns (5) and (6) present 2SLS estimates with fixed effects. Standard errors are robust to heteroskedasticity and autocorrelation. In column (5), inequality is instrumented through the average of the Ginis of the other countries in the sample, as $avg.gini(n-i)$. In column (6), the instrument is the product of inequality in Sweden and the cultural proximity of each country with Sweden, $gini_{\text{Sweden}} \times proxSweden$. With system GMM, AR(1) and AR(2) report the p-values of the Arellano–Bond test for autocorrelation of the residuals. The null of the Hansen J test (of overidentifying restrictions) is that the instruments are valid. The null of the Kleibergen–Paap (KP) LM test is that the equation is underidentified. The Kleibergen–Paap Wald *rk* F-statistic can be used to assess the strength of the instruments. The bottom part of the table reports the turning points of the inequality effect and the results of the Sasabuchi–Lind–Mehlum (SLM) test for a hump-shaped relationship. Ginis are sourced from the SWIID. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In columns (2) and (3), we deal with a possible simultaneity bias by instrumenting *gini* and *gini*^{2} through their second- and third-period lags.[15] Column (3) additionally includes a lagged dependent variable to capture feedback effects, which could be running from past saving toward current inequality. Regardless of the choice of a static or a dynamic specification, our results show a highly significant concave relationship between inequality and saving, with a turning point at a Gini of roughly 28.5. The test statistics show that the instruments are both relevant and orthogonal to the error term. Above all, the Hansen *J* test does not reject its null of instrument orthogonality (*p*-value of 0.26 in the static and 0.74 in the dynamic model), whereas the Kleibergen–Paap *rk* LM statistic rejects the null of underidentification (*p*-value of 0.03 in both models). The relevance of the instruments is also underlined by the Kleibergen–Paap *rk* Wald *F*-statistics of 63 and 64, which suggest a maximal relative IV bias of less than 5 percent. Whereas the large and highly significant coefficient of the lagged saving rate indicates a high degree of persistence, the coefficients of the other regressors are considerably smaller than in the static models. However, in dynamic models, the coefficients of the saving determinants only capture short-run effects, which can be difficult to measure, as a large share of variation is captured by the lagged dependent variable.

When dynamic fixed effects models are applied on short panels, the coefficient of the lagged dependent variable y_{it-1} is correlated with the error term and thus downward biased (see Nickell, 1981). Although such a dynamic panel bias should be very small due to the long time dimension of our panel, we follow the convention in the literature (e.g. Loayza *et al.*, 2000; Grigoli *et al.*, 2014) by also reporting system GMM estimates. The system GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) is an advancement of the difference GMM estimator (Arellano and Bond, 1991), which applies a first-difference transformation to eliminate the country fixed effects. To circumvent a dynamic panel bias, second and higher lags of the dependent variable (in levels) are used as instruments for $y_{it-1}-y_{it-2}$. The other endogenous regressors ($X_{it}-X_{it-1}$) are also instrumented via their second and higher lags. One weakness of difference GMM is a poor performance in finite samples and with persistent dependent variables. To mitigate this problem, system GMM adds an additional equation in levels, thus building a system of two simultaneous equations. For the levels equation, lagged first differences are used as instruments, assuming that the additional instruments are orthogonal to the fixed effects.

Column (4) presents the result from our system GMM estimation. To mitigate an over-fitting of endogenous variables with too many instruments, we apply a collapsed instrument matrix (see Roodman, 2009b) and restrict the instruments for the transformed equation to lag 2 and lag 3. We treat *incgrow*, *interest*, *fiscal*, *gini*, and *gini*^{2} as endogenous, while the dependency ratio is regarded as exogenous. To maximize the sample size in our unbalanced panel, orthogonal deviations are used instead of the first-difference transformation.

With system GMM, the short-run effects of *gini* and *gini*^{2} remain significant and the SLM test indicates a hump-shaped relationship with a turning point at a

[15]We use the Stata xtivreg2 routine of Baum *et al.* (2003) and Schaffer (2010) to estimate a 2SLS model with fixed effects and cluster-robust standard errors.

Gini of roughly 29. Yet, as the instruments are rather weak, the results are less reliable compared to the dynamic 2SLS estimator.[16]

Altogether, the results from lag identification and 2SLS confirm the existence of a non-monotonic effect of inequality on saving, regardless of whether a static or a dynamic specification is applied. With system GMM, the results are quantitatively similar to the dynamic FE model, but associated with a somewhat larger degree of uncertainty. Following Roodman (2009a), we would suggest that the 2SLS fixed effects estimator is more appropriate than system GMM, because of the relatively large time dimension of our panel.[17] In either case, as our particular interest lies in the medium to long-run relation between inequality and saving, we prefer the static over the dynamic model specification.

The use of internal instruments is sometimes criticized. Yet external instruments are often not valid (Bazzi and Clemens 2013) or do not show enough time variation to be applicable as an instrument for income inequality in a panel context. In such a case, it is possible to instrument a variable with its value in other countries, assuming that trends in inequality are related across nations, whereas the saving rate in one country is not related to the level of inequality in other countries. Along the lines of Checherita-Westphal and Rother (2012), we use the average inequality levels of the other OECD countries as an instrument for income inequality. In addition, we apply the level of inequality in Sweden as an alternative instrument, which has the advantage that its relevance is less affected by the unbalanced structure of our panel.[18] To improve the strength of this instrument, inequality in Sweden was multiplied by each country's cultural proximity to Sweden.[19] Columns (5) and (6) report the results from 2SLS estimations using these instruments. Both models show a highly significant hump-shaped relationship between inequality and saving and also the turning point is again located at a Gini of around 28 or 30. With regard to the relevance of our instruments, the Kleibergen–Paap F-statistic suggests an maximal IV bias of less than 15 percent in both models.

Alternative Inequality Measures

So far, we have measured inequality exclusively via the Gini coefficient, which is a very broad measure of income inequality. In this section, we test

[16]Standard specification tests for system GMM are given at the bottom of the table. Most importantly, the AR(2) p-value confirms the model specification by not rejecting the null of no second-order autocorrelation in the error term. However, the Hansen J test rejects its null at the 10 percent level, which may cast doubt on the validity of the instruments. Following Bazzi and Clemens (2013), we also present Kleibergen–Paap LM statistics and Kleibergen–Paap F-statistics for the equation using forward orthogonal deviations and for the level equation, respectively. While the KP LM test rejects the null of underidentifications, the KP F-statistic is rather low, suggesting that identification might be weak.

[17]Apart from the fact that the large time dimension mitigates the dynamic panel bias with a fixed effects estimator, a large T potentially results in an over-fitting problem due to instrument proliferation with system GMM. While over-fitting could be avoided by collapsing the instrument matrix, the latter results in weaker instruments and less reliable estimates.

[18]When a variable is instrumented by its value in other countries, its strength as an instrument is affected by the selection of countries in the panel. We thus limit our panel to the 1970–2013 period for regressions (5) and (6), as our panel is highly unbalanced, with only very few countries offering data from the 1960s.

[19]This approach was inspired by Nunn and Qian (2014). Cultural proximity to Sweden is measured by the four cultural dimensions from Hofstede (2001), as proposed in Gründler and Krieger (2016).

whether a hump-shaped relationship also occurs with alternative measures of income distribution.

In column (1) of Table 6, we start by applying the Atkinson index (*atk*) with a weight factor of one. In column (2), we use the S80/S20 ratio, which represents the share of total household income received by the top quintile divided by the income share of the bottom quintile. Columns (3)–(5) present the P90/P10 and the P90/P50 interdecile ratios, which measure the spread between high and low, or high and middle incomes. All the variables were sourced from the LIS Key Figures, apart from the S80/S20 ratio, which comes from the World Bank's WDI database. Next to these survey-based measures of inequality, we also use the income share of the richest 1 percent from the World Top Incomes Database in columns (6)–(8).

Using the Atkinson index, which summarizes the entire distribution of income, a hump-shaped relationship between inequality and saving prevails. Moreover, an increasing spread between the income shares (S80/S20) or income levels (P90/P10) of the rich and the poor also stands in a concave relationship with saving. In contrast, the spread between the income of the rich and the middle class (P90/P50) is not significantly related to saving, neither in the linear nor in the quadratic model.

A general problem with inequality data from income surveys is differential non-response (see, e.g., Atkinson and Brandolini 2001), which is why the development of top incomes is possibly not fully reflected in survey-based inequality measures. To address this problem, we deploy top-income shares from the World Top Incomes Database (WTID) of Atkinson *et al*. (2015) as an alternative inequality variable. Being generated by tax-collecting agencies, the WTID data could be more reliable than survey data. However, there are also some limitations (see Atkinson *et al*., 2011). First, top-income shares do not reflect distribution within the middle and lower ranges of the income ranking. Second, the data are based on gross incomes and ignore governmental redistribution. Third, due to diverse tax bases, income definitions, and units of observation, the data are not comparable across countries, which is why the data should not be used with estimators that exploit cross-country variations.[20]

With the top-income share, the relationship between inequality and saving becomes insignificant in the linear (column (6)) and the quadratic (column (7)) model. For the Gini, however, a hump-shaped relationship persists (column (8)), so that we can rule out that the insignificance of the top-income share merely results from the altered sample composition.

Altogether, the hump-shaped relationship appears to be robust to several alternative inequality measures. However, neither the P90/P50 decile ratio nor the income share of the richest 1 percent are significantly related to household saving. According to Frank *et al*. (2014), expenditure cascades are primarily driven by an increase in inequality at the top of the distribution. Thus, using the P90/P50 ratio or the top 1 percent income share, the insignificance of a concave relationship could be due to a more pronounced decline in the saving rates of the middle class, while the effect is not large enough to result in a significantly negative parameter

[20]In the full WTIID database, there are also some breaks within countries due to changes in tax legislation and so on. When compiling our panel, we took care to employ homogeneous series for all countries, which leads to shorter time dimensions in Finland and the United Kingdom (see the Appendix).

TABLE 6
ALTERNATIVE DATA

	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE	(8) FE
atk	195.6**							
	(75.80)							
atk^2	−605.9**							
	(240.1)							
S80/S20		4.419*						
		(2.222)						
$S80/S20^2$		−0.364**						
		(0.158)						
P90/P10			14.56**					
			(6.469)					
$P90/P10^2$			−1.660*					
			(0.817)					
P90/P50				−2.144	57.12			
				(5.943)	(44.86)			
$P90/P50^2$					−15.64			
					(12.36)			
top1inc						−0.355	0.557	−0.125
						(0.343)	(1.328)	(0.419)
$top1inc^2$							−0.0421	
							(0.0502)	
gini								2.572**
								(1.057)
$gini^2$								−0.0470**
								(0.0222)
depend	−0.684***	−0.706**	−0.660***	−0.638**	−0.643**	−0.771***	−0.805***	−0.809***
	(0.221)	(0.303)	(0.219)	(0.249)	(0.249)	(0.131)	(0.143)	(0.101)
incgrow	0.336***	0.228**	0.378***	0.338***	0.354***	0.276***	0.257***	0.217***
	(0.0908)	(0.0919)	(0.0938)	(0.0868)	(0.0821)	(0.0638)	(0.0664)	(0.0674)
interest	−0.134	0.0642	−0.127	−0.173	−0.150	−0.257**	−0.269**	−0.273**
	(0.126)	(0.185)	(0.117)	(0.113)	(0.113)	(0.107)	(0.105)	(0.0985)
fiscal	−0.452***	−0.398***	−0.470***	−0.426***	−0.437***	−0.465***	−0.505***	−0.513***
	(0.0555)	(0.0747)	(0.0666)	(0.0662)	(0.0657)	(0.0990)	(0.0910)	(0.0915)
Observations	143	151	143	143	143	430	430	427
Countries	25	25	25	25	25	18	18	18
R^2	0.482	0.456	0.465	0.428	0.434	0.602	0.608	0.637
Turning point	0.16	6.07	4.39		1.83		6.61	27.39
SLM *p*-value	0.0106	0.0407	0.0296		0.13		0.407	0.0456

Notes: The table reports fixed effects (FE) regressions. Cluster robust standard errors are in parentheses. The dependent variable is the saving rate of the household sector. The bottom part of the table reports the turning points of the inequality effect and the results of the Sasabuchi–Lind–Mehlum (SLM) test for a hump-shaped relationship. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

within a linear model.[21] The negative but insignificant estimates of P90/P50 and *top1inc* in columns (4) and (6) could be a hint for such an explanation. Yet it is also possible that the effect vanishes because both measures yield a too narrow picture of income distribution, or—in the case of the top 1 percent income share—that the measurement is too crude due to the use of gross instead of net incomes.

Different Sample Compositions

In this section, we test whether the non-monotonic relationship between inequality and saving is robust to variations in the sample composition, in addition to the reduction in sample size that results from the use of the larger regression model. First, we eliminate the top and bottom 5 percent of the distribution of saving and inequality from the regression sample. As can be seen in column (1) of Table 7, the hump-shaped relationship is robust to the omission of these outliers and also the turning point is still roughly located at a Gini of around 30.

Next, we strongly limit our sample along the cross-sectional dimension by only including the G7 economies in column (2). A similar sample has been used in previous studies (see Alvarez-Cuadrado and El-Attar Vilalta, 2012; Behringer and van Treeck, 2013), which found a negative effect of the top-income share. Yet, with our inequality data and the inclusion of the additional control variables, no clear effect of inequality emerges within the G7 sample. Whereas the signs of *gini* and $gini^2$ hint toward a hump-shaped relationship, the effects are far from significant. This is possibly due to the reduced efficiency, stemming from the very narrow sample.

In further regressions (available upon request), we test for the omission of single countries (one at a time) from the regression sample. In all these regressions, a hump-shaped relationship always remains significant and the inequality turning point varies little.

Moreover, we also check whether the effect of inequality is sensitive to different time periods. When the actual function between inequality and saving is quadratic, the estimated coefficient of inequality is downward biased in a linear regression equation. Yet the bias is small when the regression sample contains only few observations with high values of inequality.[22] As there may have been fewer instances of high inequality, this could explain why Smith (2001) has found a monotonic positive effect within the period from 1960 to 1995. To test for this supposition, column (3) reports a regression that only draws on observations from 1961–95.[23] Yet the model yields clear evidence for a hump-shaped relationship, which peaks at a Gini of roughly 28.[24]

[21]Van Treeck (2014) suspects differential effects of Ginis and top-income shares on financial stability and personal debt-to-income ratios. Behringer and van Treeck (2013) find differential effects on the current account balance.

[22]In the context of finance and growth, Arcand *et al*. (2015) offer a detailed description of the bias in linear models when the true relationship is non-monotonic.

[23]We rely on the small regression model in order to utilize the observations from the 1960s because some of the controls from the large model are not available before 1970.

[24]In a standard linear regression equation, the effect of inequality is insignificant (coefficient, 0.010; SE, 0.169).

TABLE 7
Restricted Country or Time Samples

	(1) Excluding outliers	(2) G7 countries	(3) 1961–95	(4) 1980–2013	(5) 1990–2013	(6) 2000–13
gini	3.300**	1.415	1.809**	4.110***	3.321***	0.530
	(1.404)	(1.149)	(0.821)	(0.851)	(1.062)	(1.314)
gini^2	−0.0565**	−0.0242	−0.0324**	−0.0654***	−0.0496**	−0.00379
	(0.0255)	(0.0182)	(0.0148)	(0.0139)	(0.0186)	(0.0248)
depend	−0.829***	−0.691***	−0.235	−0.801***	−0.740***	−0.265
	(0.150)	(0.154)	(0.193)	(0.163)	(0.200)	(0.157)
incgrow	0.275***	0.364**	0.231***	0.361***	0.318***	0.332***
	(0.0468)	(0.105)	(0.0762)	(0.0543)	(0.0495)	(0.0462)
interest	−0.250	0.0203	−0.376***	−0.154	−0.108	−0.0599
	(0.180)	(0.146)	(0.0900)	(0.156)	(0.165)	(0.100)
fiscal	−0.462***	−0.474***	−0.507***	−0.388***	−0.277***	−0.274***
	(0.113)	(0.115)	(0.0847)	(0.0899)	(0.0951)	(0.0567)
ln(*gdppc*)	5.622*	4.769		−3.878	−7.876	4.857
	(3.186)	(2.757)		(5.320)	(5.655)	(5.426)
infl	0.0581	0.309***		0.0373	−0.0533	−0.431***
	(0.126)	(0.0823)		(0.148)	(0.220)	(0.146)
equities	−0.0116*	−0.0136**		−0.0167**	−0.0144**	−0.0238***
	(0.00615)	(0.00447)		(0.00640)	(0.00694)	(0.00613)
houses	−0.0700	−0.0427**		−0.0751**	−0.0840*	−0.0677
	(0.0443)	(0.0149)		(0.0305)	(0.0474)	(0.0420)
credit	−0.0389**	−0.0500**		−0.00940	0.00173	−0.0126
	(0.0177)	(0.0190)		(0.0170)	(0.0141)	(0.0148)
Observations	497	212	354	560	451	291
Countries	26	7	18	27	27	27
R^2	0.513	0.846	0.335	0.560	0.496	0.380
Period	1971–2013	1971–2013	1961–95	1980–2013	1990–2013	2000–13
Turning point	29.21	29.22	27.94	31.4	33.47	–
SLM *p*-value	0.0285	0.171	0.0261	0.0004	0.034	–

Notes: The table reports fixed effects (within) regressions, with cluster robust standard errors in parentheses. The dependent variable is the saving rate of the household sector. The bottom part of the table reports the turning points of the inequality effect and the *p*-values from the Sasabuchi–Lind–Mehlum (SLM) test for a hump-shaped relationship. Column (1) drops the top and bottom 5 percent of saving and inequality; column (2) includes only the G7 economies; and columns (3)–(6) draw on different time periods. Ginis are sourced from the SWIID. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In columns (4)–(6), we continue with restricting the sample along the time dimension. More precisely, we subsequently eliminate the oldest observations, starting with the 1970s in column (4), the 1970s and 1980s in column (5), and finally also the 1990s in column (6). In the first two samples, the hump-shaped relationship remains highly significant and the turning point becomes somewhat larger. It is only in the sample that solely draws on the most recent observations that no significant effect occurs.

Semiparametric Regressions

In this section, we allow inequality to take a flexible functional form by estimating a semiparametric regression model:

$$saving_{it} = f(gini_{it}) + \beta' X_{it} + \alpha_i + \epsilon_{it}, \tag{2}$$

where the control variables X_{it} enter the model linearly and $f(gini_{it})$ denotes an unknown function of the Gini.

Our panel data regressions are based on Baltagi and Li (2002), whose estimator was built into Stata by Libois and Verardi (2013). Essentially, the estimator relies on a first-difference transformation to expunge the fixed effects (α_i) and uses OLS to estimate the parametric part of the regression equation. Afterwards, $f(gini_{it})$ is estimated via a B-spline regression model. Moreover, we apply the semiparametric estimator of Robinson (1988) with the pooled data. Robinson's estimator, which was implemented in Stata by Verardi and Debarsy (2012), partials out the parametric part of the regression equation and runs kernel regressions on the residuals. As non-parametric estimations are sensitive to outliers, we use the full set of control variables (and thus the narrower sample) for all semiparametric regressions.

Figure 3 illustrates the non-parametric part of these estimations, while the results for the linear part of the model are shown in Table A.1 (in the Appendix). The upper graph illustrates the estimated relationship from Robinson's semiparametric estimator, which we use with an Epanechnikov kernel function and cluster robust standard errors. In line with a corresponding pooled OLS estimation of a quadratic regression model (see Table A.1), Robinson's semiparametric estimator shows a hump-shaped relationship and a similar turning point, lying roughly at a Gini of around 27.

The form of the relationship is less clear when it comes to the semiparametric fixed effects estimator. The lower part of Figure 3 indicates a concave relationship when the power of the B-splines is set to $d(3)$. Yet in the default specification, with a power of $d(4)$, the graph hints toward a third-order polynomial form, where saving tends to rise again at very high levels of inequality. A direct inclusion of a cubic term into a parametric fixed effects or pooled OLS model, however, yields no significant results (see Table A.1).[25]

In sum, semiparametric regressions yield no strong evidence against a quadratic functional form. As the simple fixed effects estimator is more efficient than the semiparametric alternatives, we regard this as sufficient evidence for a hump-shaped pattern between inequality and saving. Nonetheless, we will later discuss

[25]As the estimator of Baltagi and Li (2002) relies on a first-difference transformation, while the standard fixed effects estimator is based on demeaning, the results are not directly comparable.

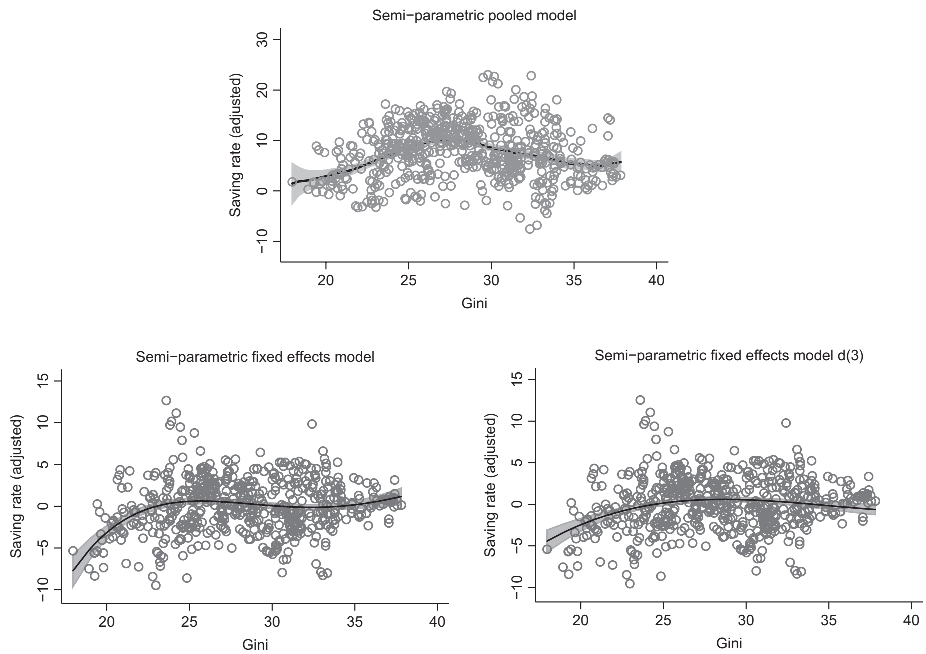

Figure 3. Partial Fit of the Relationship Between Saving and Inequality

Notes: The points on each graph are partial residuals for the household saving rate; saving rates have been adjusted for the effects of the linear control variables (see Equation 2). The partial residuals of the fixed effects regressions are centered around the mean. The shaded areas correspond to 90 percent confidence intervals.

some arguments as to why saving rates may increase with inequality when inequality is already very high.

5.3. *Interactions with Credit Availability, Financial Development, Different Time Periods, and the Income Level*

Interactions with Credit Availability and Financial Development

Along the lines of previous studies (Smith, 2001; Alvarez-Cuadrado and El-Attar Vilalta, 2012), we suppose that the relation between inequality and saving may depend on the state of financial market development. The idea is that poorer households that face a decline in relative income need credit financing to keep up with the rising consumption of the rich. The availability of credit could thus be a precondition for expenditure cascades: in countries with liberalized financial markets, expenditure cascades may dominate the link between inequality and saving, whereas Keynesian effects may prevail where credit financing is scarce. Moreover, in addition to being a precondition for expenditure cascades, credit conditions could also matter for the saving behavior of richer households: if credit is scarce, entrepreneurial households may have to save more in order to finance their investments; as a consequence, saving differentials could be more pronounced in the overall economy.

To test for the presence of such a conditional effect, we complement our baseline regression model with an interaction term, which is the product of inequality and a moderator variable measuring either credit availability or financial market liberalization:

$$saving_{it} = \alpha + \beta_1 gini_{it} + \beta_2 credit_{it} + \beta_3 gini_{it} \times credit_{it} + \beta' \mathrm{X}_{it} + \alpha_i + \lambda_t + \epsilon_{it}. \tag{3}$$

The first two columns of Table 8 report the estimates for this interaction model (excluding and including the country fixed effects) with the ratio of private credit to GDP as the moderator variable (*credit*). Indeed, both the pooled OLS model of column (1) and the fixed effects model of column (2) yield strong evidence for a significant interaction effect. In both equations, the product of *gini* and *credit* is significantly negative, while the Gini has a significantly positive coefficient.

Differentiating the equation in column (2) with respect to inequality yields the marginal effect of inequality across different levels of credit, pictured as a downward-sloping line in Figure 4. While the marginal effect of inequality on household saving is positive at low and average levels of credit, it becomes negative at a credit ratio of 130 percent. However, the surrounding 90 percent confidence intervals indicate that inequality exerts a significantly positive effect only with credit below 87 percent of GDP. Moreover, inequality only becomes significantly negative when credit is above 165 percent of GDP, a threshold which, for example, the U.S. has exceeded since the early 2000s.

Table A.2 (in the Appendix) presents the model of column (2) with the six alternative measures of income inequality that have been used in Section 5.2.3: $gini_{\mathrm{LIS}}$, the Atkinson index, S80/S20, P90/P10, P90/P50, and *top1inc*. In five of these models, the interaction between inequality and credit is negative and highly significant. Only the income share of the top 1 percent is insignificant, which could be due to the imprecise measurement of income share via gross incomes.

A possible problem arising from the use of the credit ratio as an explanatory or moderator variable is that it could be endogenous with respect to the saving rate. To circumvent this problem, we employ the financial reform index, composed by Abiad *et al*. (2010), as a measure of credit market liberalization in columns (3) and (4). Given that the financial reform index (*finreform*) is a *de jure* measure, it is free of endogeneity concerns. Yet, being based on sub-indices on subjects such as capital account restrictions, interest rate controls, and so on, the index is merely a rough proxy of credit availability.

When we substitute *credit* with *finreform* in the pooled OLS model of column (3), the signs of the coefficients of inequality and the interaction term remain unchanged. Apparently, with highly regulated financial markets (low index values) a positive marginal effect of inequality prevails, but decreases and finally becomes negative with increasing financial liberalization (high index values). Nonetheless, in the fixed effects model of column (4) the interaction effect is insignificant, which is not surprising given that most of the index variation stems from differences across countries.

TABLE 8
Interactions

	(1) POLS	(2) FE	(3) POLS	(4) FE	(5) FE	(6) FE	(7) FE
gini	1.146***	0.958***	1.332***	0.390	2.337**	3.325***	2.499***
	(0.322)	(0.295)	(0.371)	(0.338)	(0.871)	(0.971)	(0.732)
$gini^2$					−0.0261	−0.0532***	−0.0408***
					(0.0156)	(0.0163)	(0.0120)
credit	0.311***	0.185***			0.156***		−0.0195
	(0.0910)	(0.0459)			(0.0516)		(0.0163)
gini × *credit*	−0.0116***	−0.0074***			−0.00618***		
	(0.00297)	(0.00159)			(0.00175)		
finreform			0.351*	0.157			
			(0.170)	(0.109)			
gini × *finreform*			−0.0161***	−0.00614			
			(0.00543)	(0.00378)			
credithigh						17.71	
						(21.90)	
gini × *credithigh*						−0.968	
						(1.544)	
$gini^2$ × *credithigh*						0.0107	
						(0.0268)	
postcrisis							37.64
							(40.64)
gini × *postcrisis*							−2.020
							(2.616)
$gini^2$ × *postcrisis*							0.0269
							(0.0417)
Observations	616	616	451	451	616	648	616
Countries	27	27	21	21	27	27	27
R^2	0.430	0.612	0.509	0.539	0.618	0.595	0.609

Notes: The table reports pooled OLS (POLS) and fixed effects (FE) regressions, with cluster robust standard errors in parentheses. The dependent variable is the saving rate of the household sector. Control variables (*depend*, *incgrow*, *interest*, *fiscal*, *equities*, *houses*, ln(*gdppc*), *infl*) are omitted for clarity. Ginis are sourced from the SWIID. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

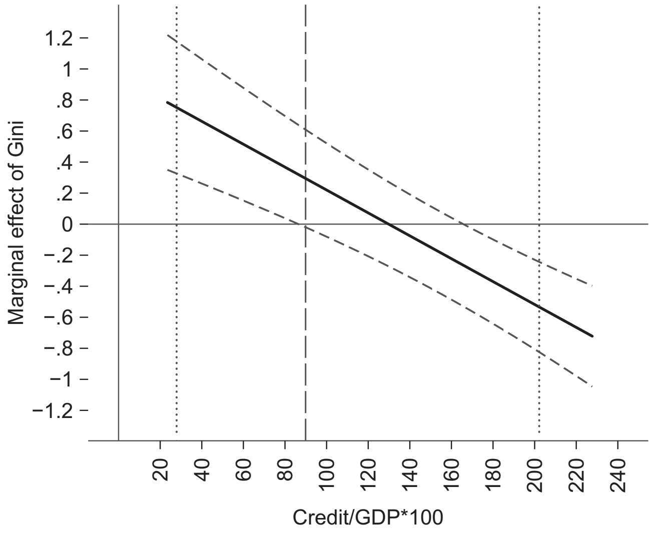

Figure 4. The Marginal Effect of Inequality on Saving Across Different Levels of Credit Availability

Notes: Values are calculated using the results from column (2) of Table 8. The downward-sloping line plots the marginal effect of inequality. The surrounding dashed lines represent the 90 percent confidence intervals. The vertical lines indicate the distribution of the credit-to-GDP ratio in the sample: the dotted lines mark the first and 99th percentiles, while the dashed line marks the median value.

As the effect of inequality depends on credit availability, it is questionable whether the concave relationship persists at different states of financial development. Hence, column (5) presents a direct test for the robustness of the concave function by adding $gini^2$ to the interaction model. Here, the interaction term is still significantly negative and the estimated coefficient of the quadratic term turns out to be marginally significant. However, we prefer an alternative approach that offers a clearer interpretation of the conditional effects of income inequality. More precisely, we test for the presence of heterogeneous effects by including a dummy variable, *credithigh*, which we set as 1 for values of credit to GDP above the sample median of 90 percent.[26] Then, we effectively split our sample into a low-credit and a high-credit subsample by estimating the following model:

$$saving_{it} = \alpha + \beta_1 gini_{it} + \beta_2 gini_{it}^2 + (\beta_3 gini_{it} + \beta_4 gini_{it}^2 + \beta_5) \times credithigh_{it} + \beta' \mathrm{X}_{it} + \alpha_i + \lambda_t + \epsilon_{it}. \tag{4}$$

Column (6) of Table 8 reports our estimates for this model. The effect of inequality in country–years with a low level of credit can be directly seized via β_1 and β_2, which indicate a significant hump-shaped relationship. At high levels of credit, $\beta_1+\beta_3$ and $\beta_2+\beta_4$ measure the inequality-saving relationship, indicating a concave relationship that is somewhat less pronounced than in the low-credit subsample.

[26]The estimated coefficient of *credithigh* (−1.012) is insignificant (*p*-value: 0.131) in a model where *credithigh* serves as an additional regressor, but not as a moderator variable.

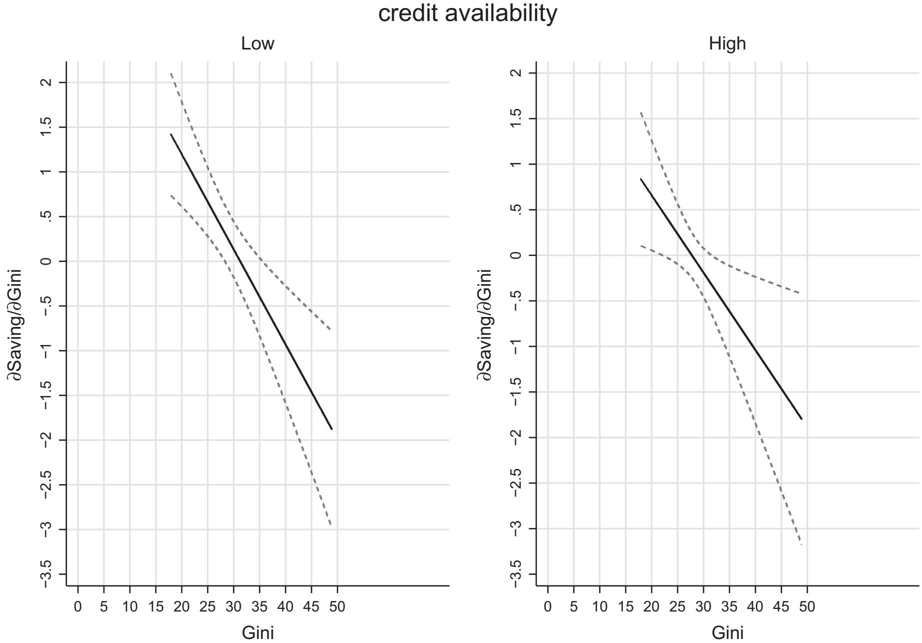

Figure 5. The Marginal Effect of Inequality on Saving with Low and High Credit Availability (Below and Above 90 Percent of GDP)

Notes: Values are calculated using the results from column (5) of Table 8. The downward-sloping line plots the marginal effect of inequality at different levels of inequality. The surrounding dashed lines represent the 90 percent confidence intervals.

Based on the results from column (6), Figure 5 illustrates the marginal effect of inequality at low and high levels of credit together with the 90 percent confidence intervals.[27] It shows that the Gini at which the marginal effect of inequality turns from positive to negative is somewhat higher in the low-credit group.[28] Moreover, very tight 90 percent confidence intervals in the low-credit subsample indicate that inequality exerts a significant positive effect on saving at a wider range of inequality values. Within the high-credit group, inequality yields a significantly positive effect only at very low levels of inequality and becomes significantly negative for values of the Gini above 33.

Altogether, we find that the relation between inequality and saving tends to be positive with low credit availability and negative with high credit availability. Nonetheless, a hump-shaped relationship between inequality and saving prevails in both low- and high-credit environments.

Inequality and Saving After the Financial Crisis

Given that the risks of subprime lending to poorer households became obvious with the 2008–10 Global Financial Crisis (see, e.g., Rajan, 2010), the ability

[27]In the course of generating this figure, we benefited from the code provided by Arcand *et al.* (2015).

[28]The turning point is 31 in the low-credit group and 28 in the high-credit group.

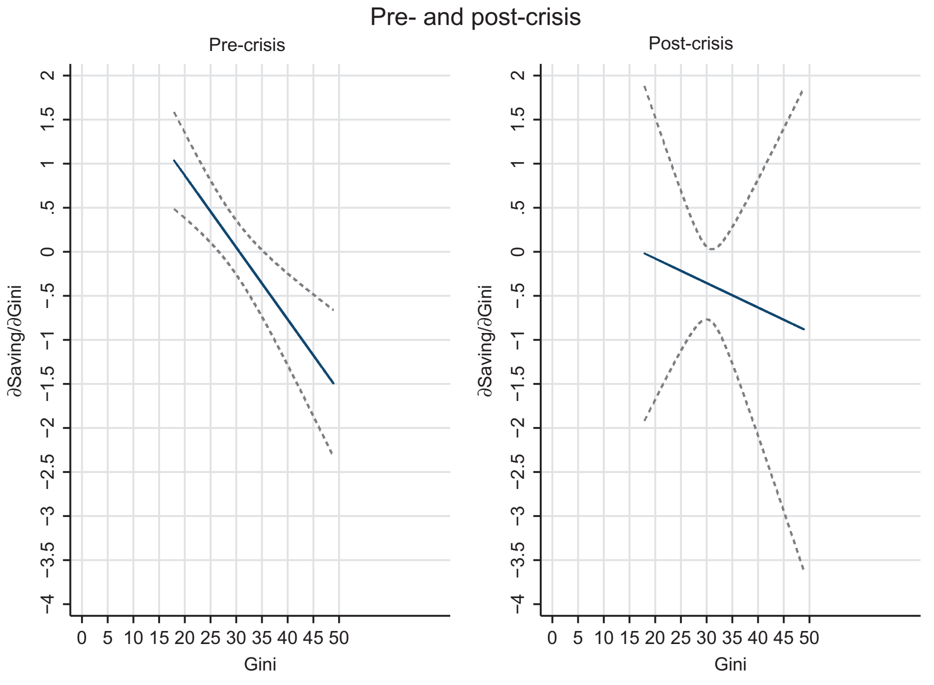

Figure 6. The Marginal Effect of Inequality on Saving Before and After the Global Financial Crisis (Before and After 2008) [Colour figure can be viewed at wileyonlinelibrary.com]

Notes: Values are calculated using the results from column (6) of Table 8. The downward-sloping line plots the marginal effect of inequality at different levels of inequality. The surrounding dashed lines represent the 90 percent confidence intervals.

and willingness of poorer households to engage in expenditure cascades may have decreased. Thus the negative part of the hump-shaped relationship between inequality and saving may have vanished in the post-crisis period.

To test for this supposition, we create a dummy variable (*postcrisis*), which we set as 1 for all observations after 2007. Then, we effectively split our sample into a pre-crisis and a post-crisis subsample by estimating a nested regression model, similar to Equation 4.[29]

The results for *gini*×*postcrisis* and *gini*×*postcrisis*^{2} in column (7) of Table 8 indicate that the estimated coefficients of inequality have declined after the outbreak of the crisis. Yet the interacted terms are statistically insignificant and smaller than the main effects. Figure 6 plots the marginal effects of inequality received from the estimated equation. It shows that before 2008, inequality had a significantly positive effect on saving if the value of the Gini was below 25, a null effect at a Gini of around 30, and a significantly negative effect at Ginis above 35. In contrast, inequality never exerted a significant effect in the post-crisis period—which, however, could be due to the small number of observations in the subsample.

[29]The most recent observations in our panel are from 2013, so that the post-crisis dummy marks all observations from 2008 to 2013.

Interactions with the Income Level

Following Smith (2001), we also test whether the effect of inequality depends on the level of average per capita income.[30] For instance, such a conditional effect could be related to the subsistence consumption argument. As argued in Section 2, a subsistence consumption level above the income of poorer households could be one reason for differential saving rates across households.[31] According to Musgrove (1980) and Smith (2001), this implies that the effect of inequality on saving could depend on the current income level of the economy. In poorer countries, where a significant share of households live below subsistence, increasing inequality may lift some households above subsistence so that saving rates increase on aggregate. In rich countries, however, the same increase in inequality may have a smaller effect, as subsistence consumption is already very rare.

In the benchmark fixed effects model of column (2) in Table 9, but also in most alternative specifications, an interaction term of inequality and real income per capita is significantly negative, indicating a positive effect of inequality that vanishes when countries become richer. While this finding supports the subsistence consumption argument, it could, however, also be related to the interactions that we have observed before. In fact, as it is well documented that the financial system typically expands when countries become richer (e.g. Demirgüc-Kunt *et al.*, 2013), the income level might merely pose a proxy for financial development and the ease of credit financing.

5.4. *Private Saving, National Saving, and the Current Account*

Finally, we analyze whether the effect of inequality on household saving transmits to broader measures of saving and the current account balance. Although our theories of interest refer to household behavior, if richer households were to maintain a large volume of saving within incorporated enterprises, the household saving rate would be too narrow. As it includes saving from both the household and the corporate sector, the use of private saving rates could thus be beneficial. Following previous cross-country studies on inequality and saving, we also look at national saving rates, which include saving by the government. National saving could be of interest, as it measures the total amount of saving in the economy. Yet, its application is problematic if fiscal policy exerts offsetting effects.

Referring to studies that motivate our paper, we finally check whether the link between inequality and saving transmits to the current account. Being the balance between national saving and investment, we would expect that inequality has a similar influence on the current account as it has on saving.

Table 10 presents the results of regressions for these alternative dependent variables. To enhance comparability, each column draws on a uniform sample of 517 observations. The regressors are identical to the small fixed effects model from our

[30]We would also like to thank an anonymous referee for suggesting this specification.

[31]Subsistence consumption may not only comprise the necessities for sheer survival but, rather, may depict a socially acceptable minimum consumption level that can also be missed in richer countries.

TABLE 9
INTERACTIONS WITH THE INCOME LEVEL

	(1) POLS	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE
gini	0.125	1.508**				
	(0.602)	(0.630)				
gini × *gdp*	−0.000006	−0.000033**				
	(0.000016)	(0.000015)				
atk			108.8**			
			(40.90)			
atk × *gdppc*			−0.00242**			
			(0.000951)			
S80/S20				4.211***		
				(1.116)		
S80/S20 × *gdppc*				−0.000099***		
				(0.000023)		
P90/P10					6.831***	
					(1.845)	
P90/P10 × *gdppc*					−0.00011*	
					(0.000054)	
P90/P50						18.67**
						(7.686)
P90/P50 × *gdppc*						−0.00044*
						(0.000228)
gdppc	0.000303	0.00101**	0.000327	0.000503*	0.000345	0.000763
	(0.000437)	(0.000453)	(0.000302)	(0.000276)	(0.000378)	(0.000561)
Observations	451	451	88	90	88	88
Countries		27	24	23	24	24
R^2	0.153	0.494	0.544	0.602	0.566	0.530
$\frac{\delta saving}{\delta ineq} = 0$	–	46,115	44,879	42,580	62,381	42,490

Notes: The table reports fixed effects (FE) regressions with cluster robust standard errors in parentheses. Dependent variable is the saving rate of the household sector. Control variables (*depend*, *incgrow*, *interest*, *fiscal*, *equities*, *houses*, *infl*, *credit*) are omitted for clarity. $\frac{\delta saving}{\delta ineq} = 0$ presents the per capita level of GDP where the marginal effect of inequality turns negative. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 10
Alternative Dependent Variables

	(1) Household saving	(2) Private saving	(3) National saving (net)	(4) National saving (gross)	(5) Current account
gini	3.057***	2.755**	3.086***	1.894***	2.602***
	(0.865)	(1.060)	(0.843)	(0.494)	(0.709)
$gini^2$	−0.0547***	−0.0461**	−0.0497***	−0.0333***	−0.0436***
	(0.0123)	(0.0167)	(0.0138)	(0.00811)	(0.0123)
depend	−0.814***	−0.351*	−0.650***	−0.277*	0.131
	(0.279)	(0.185)	(0.164)	(0.142)	(0.122)
incgrow	0.296***	0.316***	0.470***	0.247***	−0.140*
	(0.0622)	(0.0854)	(0.0644)	(0.0830)	(0.0711)
interest	−0.0405	−0.0522	−0.282***	−0.339***	−0.00218
	(0.179)	(0.109)	(0.0938)	(0.115)	(0.120)
fiscal	−0.524***	−0.360***			0.0112
	(0.0964)	(0.0779)			(0.0665)
Observations	517	517	517	517	517
Countries	25	25	25	25	25
R^2	0.439	0.310	0.419	0.238	0.0939
Turning point	27.93	29.88	31.06	28.43	29.83
CI 90%	[22.68; 30.91]	[24.91; 33.03]	[28.18; 34.60]	[24.56; 31.89]	[26.93; 33.75]
Slope: $gini_{\text{min}}$	1.09**	1.1**	1.3***	0.69***	1.03***
Slope: $gini_{\text{max}}$	−2.31***	−1.76***	−1.78***	−1.37***	−1.67***
SLM *p*-value	0.0104	0.0148	0.0018	0.0025	0.0022

Notes: The table reports fixed effects (within) regressions, with cluster robust standard errors in parentheses. The bottom part of the table reports the turning points of the inequality effect and the results of the Sasabuchi–Lind–Mehlum (SLM) test for a hump-shaped relationship. CI 90% denotes the 90 percent Fieller confidence intervals for the turning point. Slopes at $gini_{\text{min}}$ and $gini_{\text{max}}$ are uniformly measured at Ginis of 18 and 49. Ginis are sourced from the SWIID. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

baseline table. Yet, as it is too closely related to public saving, which is part of the dependent variable, we drop the fiscal balance in the regressions for national saving.[32]

As a benchmark reference, column (1) repeats the baseline household saving regression, which is now based on the uniform sample. Column (2) reports results for the net private saving rate. Both columns (3) and (4) cover national saving rates: in column (3), national saving is measured net of fixed capital depreciation, in line with the concept that we adopt throughout this paper. Yet most previous studies use gross national saving rates, which we utilize in column (4). Finally, column (5) reports results for the current account balance. The Appendix describes the sources and derivations of the new dependent variables.

For each saving aggregate, our results indicate a non-monotonic effect of inequality and the SLM test always confirms the existence of a hump-shaped relationship. Moreover, the shape of the relationship is always similar, with minor differences. For net private saving, and even more so for net national saving, the effect of inequality appears to be positive at a wider range of Ginis. Yet, for gross national saving, the turning point of the hump-shaped relationship is again close to the peak value from the household saving regression. Even for the current account balance, the effect of inequality is similar to the one we know from the household saving

[32]One could also argue that the fiscal balance is a direct component of the current account balance. Yet, because it is frequently used in the current account literature, we keep the fiscal balance as a regressor in column (5).

regressions. Apparently, the current account increases with rising inequality, if inequality is low, whereas it tends to decrease when the Gini becomes larger than 30.[33]

Finally, we also utilized different inequality measures in each of the regressions with alternative dependent variables. The results, which are given in Table A.3 (in the Appendix), confirm the patterns that have emerged in Table 10. Yet, whereas a hump-shaped relationship is highly significant in most cases, it never occurs when inequality is measured via the income share of the top 1 percent. In contrast to its insignificance in the household-saving regressions, however, the P90/P50 ratio is correlated with national saving and the current account balance in the usual non-monotonic way. In general, the regressions attest to a strong robustness with regard to the choice of different inequality measures.

In sum, the impact of inequality on household saving rates appears to transmit to broader saving aggregates. Moreover, although the drivers of current account balances are not the primary focus of this paper, our results also hint that inequality affects the current account in a non-monotonic way.

6. Discussion and Conclusion

This paper shows that the marginal effect of inequality on saving varies with the level of credit availability, the state of financial liberalization, and the income level of the economy. Above all, however, we find that the relationship between inequality and aggregate saving is hump-shaped, meaning that with higher levels of inequality, an initially positive marginal effect of inequality decreases and eventually becomes negative.

An explanation for the decreasing marginal effect of inequality could be given by a non-linear adaption in household consumption behavior: if inequality only becomes gradually visible, the saving rates of poor and middle-class households possibly remain unchanged, while inequality is still rising from a low level. Thus aggregate saving would initially be dominated by an increasing income share of households with a high propensity to save. As inequality rises further, this positive effect on saving could be increasingly compensated by a changing behavior of households from the middle and lower ranks of the income distribution. When inequality becomes more and more visible, the incentive to engage in conspicuous consumption rises until the decrease in saving of poorer households dominates in aggregate.

Moreover, at high levels of inequality, further gains in inequality could increasingly result from a decline in the real income of poorer households. At some point, income may fall below a level that suffices to finance saving plus socially acceptable minimum consumption. Income losses will then be compensated by a reduction of the saving rate. When the latter starts to offset the direct effect from rising income concentration, the marginal effect of inequality on aggregate saving decreases and after some point becomes negative.

Finally, the non-monotonic relationship between inequality and saving could also be related to the saving behavior of richer households. If the gap between rich and poor is rather small, the rich may want to save more in order to maintain a

[33]The hump-shaped relationship also prevails with the full set of covariates and an unrestricted sample. The results are available upon request.

living standard that possibly appears to be more uncertain. In highly unequal societies, however, their saving incentives may be lower, as a superior living standard is taken for granted.[34] While this paper rests on the distribution of income, progress in data availability could allow future research to test whether the distribution of wealth contributes to such an explanation.

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Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's web site:

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Appendix A2 Semiparametric and 3rd order polynomial regressions
Appendix A3 Regressions with alternative inequality measures
Table 1 Semiparametric and 3rd order polynomial regressions
Table 2 Interactions between credit and alternative inequality measures
Table 3 Alternative dependent variables and different measures of inequality