Household Debt, Consumption and Inequality

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Abstract

This paper examines the link between household credit shocks, consumption and income inequality at the national level. Empirically, we use country-specific VAR models to estimate the dynamic responses of aggregate consumption to household credit shocks. We then show in cross-country regressions that the consumption response is more sensitive to such shocks in countries with higher levels of inequality, even after controlling for financial development. Theoretically, we construct and simulate a dynamic model based on the effect of inequality on the incidence of credit constraints, to illustrate potential causal mechanisms.

Keywords: Credit constraints, credit shocks, income distribution, VAR, Gini coefficient, local projections

JEL codes: E21, E32, E44, E51

1 Introduction

The recent work of Mian, Sufi, and Verner (2017) and others documents the importance of household debt as a driver of business cycles for developed and emerging-market economies. Household debt appears to work through a 'household demand channel' (Mian, Sufi, and Verner, 2019) and affects both the boom and bust of a debt cycle. During the boom, household borrowing increases consumption and contributes to an increase in economic activity; but such borrowing ultimately brings about a bust as households retrench in the face of mounting debt. A consensus has emerged that household debt can generate short-term gains but at a cost of significant reductions in medium- to long-term growth. We do not yet, however, have a complete picture of the economic mechanisms at play.

Our paper aims to add to this picture by looking at the relationship between household debt and aggregate consumption from a different angle than most previous studies. In particular, we examine the extent to which income inequality contributes to the household demand channel in response to household credit shocks. Section 2 of the paper takes this question to the aggregate data. We first estimate the dynamic effects of household credit shocks on aggregate consumption for a sample of 32 countries, using standard VAR techniques and treating countries individually. We show that household credit shocks tend to have positive effects on consumption – which most likely indicates the importance of binding credit constraints at the aggregate level – but that these effects die out over time and for some countries eventually become negative. This finding is consistent with most of the related literature. We then run cross-country regressions to gauge the effect of income inequality, as measured by country-specific Gini coefficients and other similar measures, on the sensitivity of consumption to household credit shocks estimated in the first stage of the data analysis. We show that, even after controlling for financial development and other potential confounding factors, countries having higher Gini coefficients than other countries, and thus more unequal income distributions, exhibit greater short-run gain and greater medium- to long-run pain from household credit shocks. The results and inference are robust to alternative measures of inequality. Thus, we find a robust and plausible causal empirical link between income inequality and the household demand channel.

Section 3 of the paper develops a simple theoretical model to illustrate how variation in income inequality can cause variation in consumption responses to credit shocks. The model relies on financial market imperfections and credit constraints to motivate a link between inequality and the incidence of household credit shocks. In the model, the burden of credit constraints depends on a household's income – high-income earners never face a borrowing constraint and low-income earners always do. Middle-earners, however, may be credit constrained (like low-earners) if their income level is sufficiently low, but they can be unconstrained (like high-earners) if their income is sufficiently high. The model implies that if the income share of middle-earners falls, the country's income distribution becomes more unequal (the Gini coefficient rises) at the same time that there is an increase in the number of households that are credit constrained. This increase in the incidence of credit constraints further implies that credit shocks have larger aggregate effects on consumption the greater is income inequality. We simulate the model to show that this mechanism can explain the shapes and magnitudes of the impulse response functions estimated from the data.

Our focus in this paper is on *income* inequality, and not *wealth* inequality. We show empirically that wealth Gini coefficients have similar effects on the consumption responses we estimate; however, these effects are weaker and more uncertain than for income inequality. This finding might be due to less reliable data or an actual weaker link to the incidence of credit constraints, but motivates our focus on the distribution of income in our empirical and theoretical work. In addition, while the distribution of wealth (particularly housing) has played a role in the literature on credit constraints, much of this literature has relied on the assumption that credit is constrained by income alone. The relationship between wealth inequality, consumption and credit constraints – and how that relationship differs with income inequality – deserves further study in future research.

Our work contributes to the vast literature on understanding the effects of credit supply shocks on the overall economy. In addition to the two papers cited in the first paragraph, an abbreviated list of recent related research includes Mian and Sufi (2018), Justinian, Primiceri, and Tambalotti (2015), Favilukis, Ludvigson, and Van Nieuwerburgh (2017), Gennaioli, Shleifer, and Vishny (2012), Schmitt-Grohé and Uribe (2016), Korinek and Simsek (2016), Farhi and Werning (2016), Bahadir and Gumus (2016), Cloyne et al. (2019) and Abdallah and Lastrapes (2012). Only a handful of papers in this area specifically consider income distribution and inequality as an important factor for the effects of debt. In a strictly empirical study, Alter, Feng, and Valckx (2018) show that the mortgage-debt share of lower income households – as a measure of unequal access to financial markets – affects the relationship between household debt and growth. However, that paper neither examines other measures of inequality nor links the findings to specific theory. Kumhof, Ranciere, and Winant (2015) show that higher leverage and crises arise endogenously in response to a growing share of high-income households, but do not account for the important difference – documented in much of the studies noted above – between household and firm debt. Iacoviello (2008) shows that the prolonged rise in household debt in the US can be explained only by the concurrent increase in income inequality, a finding supported by Kumhof, Ranciere, and Winant (2015), although our paper is agnostic about whether economies with high income inequality experience faster growth in household debt.

2 Empirical analysis

2.1 Estimating the dynamic response of consumption to credit shocks

In the first part of the data analysis we estimate country-specific dynamic responses of real aggregate consumption to household credit shocks. We do so in the baseline case by inverting estimated VAR models to obtain impulse response functions, and then checking for robustness to model misspecification using the local projections approach of Jorda (2005) to estimate impulse response functions directly. In the baseline model we separately estimate, for each of the 32 countries in our sample, a VAR model that includes the log of real consumption, the ratio of non-financial firm debt to GDP, and the ratio of household debt to GDP. We use the same variables in the local projections estimations. We choose this three-variable system to be comparable to Mian, Sufi, and Verner (2017).[1] The data are seasonally-adjusted quarterly observations over a sample period from 1990 to 2017, where the first and last observations vary within this range across countries based on data availability.[2] Table 1 lists the countries in the sample and their sample periods, as well as sample means for the variables in the model. Figure 1 plots the time series themselves for each country.

Because we focus on the impulse responses to a household credit shock only (and not firm-credit or consumption shocks), we need not fully identify the empirical model. Instead we impose only two identifying restrictions that are sufficient to just-identify the structural shocks of interest: we assume that neither consumption nor the firm debt ratio responds contemporaneously to household credit shocks. The assumption that consumption is slow to respond to credit shocks is standard in the related literature, see for example Mian, Sufi, and Verner (2017, p. 1764). The second restriction defines a *household* credit shock as one that has an immediate effect on household debt – either the demand to borrow by or the supply of funds to households, such as a loosening or tightening of borrowing limits for consumer credit – but that does not directly affect, on impact, the demand for or supply of *firm* debt. These restrictions can be implemented using the standard Cholesky decomposition of the reduced form residual covariance matrix estimated from the VAR, using the ordering noted above. Thus, our results are based on a minimal set of identifying restrictions and should therefore be consistent with a wide range of theoretical models.[3] Although our approach to

[1] Estimating separate VAR models for each country in the sample is less restrictive than the panel approach of Mian, Sufi, and Verner (2017). In effect, our approach is tantamount to estimating a panel model that includes fixed effects dummy variables that interact with ALL lagged right-hand-side variables in the system.

[2] Household and non-financial firm debt are from the "Long series on credit to the private non-financial sector" database of the Bank for International Settlement. GDP, household consumption and Consumer Price Index (CPI) series are from the International Financial Statistics (IFS) Database. We use quarterly data in current and constant prices from the IFS and deflate nominal consumption spending by the CPI to get real consumption.

[3] As long as the household debt variable is ordered last, identification of the responses of each variable to household credit shocks does not depend on the ordering of the first two variables. Note that to identify firm credit shocks using an analogous strategy would require re-ordering firm credit as the last variable in the Cholesky ordering, so that such a shock would have no contemporaneous effect on *household* credit.

identification is standard, the online appendix provides a brief overview of these restrictions for both the VAR and local projection models.

We are aware of the shortcomings of the recursively-identified VAR approach, and of other work, such as Mumtaz, Pinter, and Theodoridis (2018), that considers alternative restrictions to identify credit shocks. However, the findings below are plausible in light of this other work, and we believe the simple, transparent and common approach to identification in the VAR model is a satisfactory strategy for our objectives. We also do not attempt at this stage to precisely identify whether household credit shocks in our model and data are demand or supply induced. Interest rate variation provides especially useful identifying information in this context (Mian and Sufi, 2018, p. 35); however, we do not have sufficient data on interest rates to perform a convincing analysis. We rely on the findings of Mian, Sufi, and Verner (2017) that credit supply shocks, as opposed to demand, are most likely driving our results.

Our baseline VAR model for each country includes four lags of that country's variables and a deterministic linear time trend, which is sufficient in all cases to whiten the residuals. All of our findings and inference are fully robust to using alternative common lag lengths of two, three, five and six. Because of the inclusion of the time trend, the dynamic responses generated from these models should be interpreted as deviations from trend. In many cases, but not all, log consumption and the credit ratios exhibit unit roots. We have chosen to maintain our specification of the levels (not differences) of the variables because this is the least restrictive specification, and we do not perform formal statistical tests on the parameters of the VAR models where a mixed-order of integration might matter.

We report the impulse response functions estimated from our baseline VAR models for each country in Figures 2 and 3, which plot the dynamic responses of both the log of real consumption and the household credit ratio to a household credit shock up to a 24-quarter horizon. The first figure shows responses to a unit shock, the second to a standard deviation shock. We look at the first case to compare responses across countries to shocks of a common

Simply interpreting the shock from the second equation from the original ordering as a firm credit shock is misleading since its impact effects on both firm and household debt would not be restricted in this case.

magnitude. The second case accounts for potential differences in the scale of credit shocks across countries.[4]

By construction the immediate effect of a unit household credit shock, as seen in the first figure, is to increase the household credit ratio by one percentage-point on impact for each country (red curve), but the data determine the estimated dynamics of the response over the remaining horizons. For most countries the response of the household credit ratio is persistently positive over the short- to medium-run, but the degree of persistence varies widely across countries. For countries like Australia, Germany and the US, household credit as a fraction of GDP remains well above its initial steady-state up to 24 quarters after the shock; for others, like Japan, Russia and Switzerland, household credit relative to GDP rises in the short-run but falls below its initial steady state after two to three years.

There is variation in the consumption response across countries as well (blue curve). Our recursive identification scheme forces the impact effect of consumption to be zero for all countries, but the data show that consumption tends to rise in the short-run beyond the impact horizon. Indeed, for 24 of the 32 countries in the sample the consumption response is positive at some point over the first two years after the shock. For the US, the maximum consumption response to a household credit shock that initially increases household credit by 10 percentage points (for example, from the US mean household credit/gdp of 76.8% to 86.8%) is 6%, which happens at the eight-quarter horizon. For the UK, the maximum consumption response to a local household credit shock of the same magnitude is around 8% for a similar horizon.

An evident pattern from the figure is that domestic household credit-to-GDP expansion in the emerging market economies in our sample – Argentina, Brazil, Mexico, Russia and Turkey – leads to a relatively large household spending response in the short run. Consumption in Argentina, for example, rises by almost 7% in response to a *one* percentage point household

[4] Because we attempt to explain cross-country variation in the next stage of the analysis, and to avoid graphical clutter, we do not report standard error bands in these figures. However, standard error bands computed using standard Monte Carlo integration methods are reported in Figures A1 through A4 of the online appendix.

credit ratio shock, an order of magnitude more than the US consumption increase. The maximum responses of Brazil, Mexico, Russia and Turkey are in the range of 1.5 to 2.5%, all within the first year after the shock. Argentina and Russia also exhibit large busts in consumption over the medium run. In Russia, the credit boom leads to an ultimate decline in output of nearly 10%, which in Argentina is over 3% between three and four years after the shock. Consumption booms in the short run and busts in the long run in Italy and Greece are pronounced as well. Thailand experiences a large bust but a smaller boom than the other emerging market economies.

We investigate the source of this cross-country variation in more detail below, but one potential explanation for these differences is that a given percentage-point increase in the household debt-to-GDP ratio is relatively large for the developing nations given their small average household debt ratios. In Argentina, for example, this ratio is 5% on average over our sample, compared to 77% in the US (see Table 1). Average debt ratios in the other four countries range from 7% to 16%. A ten percentage point increase in a country with a 10% debt-income ratio is a doubling of that ratio; the same percentage point increase for a country with an 80% ratio is only a 12.5% increase. This explanation is less plausible for Italy, Greece and Thailand, since their debt ratios range on average from 30% to 50%.

Figure 3 accounts for this difference in the scale of household credit across countries by normalizing on standard deviation shocks. By construction, the shapes of the response functions will be identical across the two figures, but the magnitudes measured along the vertical axis can differ. The figure shows that accounting for the estimated scale of credit shocks across countries does not alter our inference. For example, the consumption responses in Argentina and Brazil remain more than double the size of the US response, even though average shock size is smaller in the former countries.

Figure 4 summarizes the dynamic responses of consumption to the unit household credit shocks from the first figure to better illustrate the cross-country variation in those responses. The top panel plots the responses at horizons 2 (the period after the initial shock), 4, 8, 12, 16, 20 and 24 quarters. The solid red curve is the cross-sectional mean response across the sample of 32 countries for each horizon from 1 to 24. The mean positive response in the short run and negative response over the medium to long run are consistent with the boom-bust hypothesis of household credit shocks, and are similar to the aggregate responses of GDP as reported by Mian, Sufi, and Verner (2017, Figure 1, p. 1765). The extreme values in Argentina and Russia are evident in the graph, but there is substantial variation across the responses of the other countries as well. The bottom panel contains each country's peak response, at the horizon at which that peak occurs (with the cross-sectional mean again superimposed).

As noted above, we consider the robustness of our results from the VAR model to those using local projections methods. Figures A1 through A4 in the online appendix allow a direct visual comparison of the impulse response functions estimated from the two methods. While overall the local projections impulse response functions lack the smoothness of the VAR functions across forecast horizons, the shapes and magnitudes are generally comparable. There are noticeable differences, but in most cases, the local projection responses follow a similar path to the VAR responses. We also note below that our second stage results are generally robust to these methods as well.[5]

2.2 Estimating cross-country variation in the response of consumption

In this sub-section we attempt to explain the previously estimated cross-country variation in boom-bust dynamics of consumption in response to household credit shocks, focusing on the role of income inequality. We estimate the cross-sectional regression model

$$y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \epsilon_i \tag{1}$$

[5] The smoothed local projections approach of Barnichon and Brownlees (2019) would bring our local projection responses closer in line with the VAR's. Also, see the recent working paper by Plagborg-Moller and Wolf (2020) for theoretical and empirical comparisons of the two approaches to estimating response functions. They show that, under weak conditions, response functions are identical in population but can differ in finite samples.

for countries $i = 1, \cdots, 32$, where the dependent variable y_i is a summary measure of each country's dynamic consumption response to household credit shocks estimated above in the first stage VAR. The explanatory variable z_{i1} is a measure of nation-wide financial development, included as a fundamental control variable, while z_{i2} is country i's income Gini coefficient, our main inequality measure. We consider below robustness to inequality and financial development measurement, additional control variables and to local projections estimates of the dynamic responses. β_1 and β_2 measure the marginal effects of financial development and inequality on the estimated dynamic responses; our primary focus is on β_2.

Our two-stage approach to explaining cross-sectional variation in dynamic responses is more general than conventional panel data methods, since we do not impose the potentially severe constraint that parameters are identical across countries. The approach has precedents in the literature; see for example Cecchetti (1999), Lastrapes and McMillin (2004), Aizenman et al. (2019), and Herrera and Rangaraju (Forthcoming) among many others. Although the impulse responses for the dependent variable are generated from the first stage VAR estimation, measurement and specification error in that stage will be captured by the cross-sectional regression error term and will lead to biased estimates only to the extent that measurement error is correlated with the primary explanatory variables. There are no obvious reasons to expect such correlation. In addition, any heteroskedasticity introduced by the generated dependent variable into the regression error is effectively controlled for by heteroskedastic-robust standard errors.

Since we are interested in the short-run boom in consumption and the medium- to long-run bust, we run the cross-country regression separately for various measures of the dependent variable, y_i. In particular, we alternately set y_i to be the impulse response coefficient estimates on 'impact' (with a one-period lag) of consumption to the credit shock ($c_{qj}, j = 2$) and for each four-quarter horizon up to quarter 24. We also consider the maximum response over the first twelve quarters (c_{max}), and cumulative responses over the short-run (1 to 12 quarters) and medium- to long-run (12 to 24 quarters). Table 2 reports for each country the maximum response over the first twelve quarters, and responses at quarters 2, 4, 8.

To measure z_1, the level of a country's financial development, we use the index developed by Svirydzenka (2016), which combines information on the depth, access and efficiency of financial institutions and markets in that country. A higher value for z_1 indicates a higher level of financial development. While our baseline results rely on the index, we also consider robustness to including the individual elements as controls. Table 3 reports the time averages for the financial development index and its components for each country.

For income inequality, our baseline measure for z_2 is the after-tax Gini index, obtained from the Standardized World Income Inequality Database (Solt, 2016). A higher value for z_2 indicates a higher level of income inequality. We also use as alternative measures of income inequality a dummy variable set to one for the countries with the five highest Gini coefficients (Mexico, Argentina, Brazil, Thailand and Turkey), the Kuznets ratio (the ratio of income going to the top 20^{th} percentile to bottom 20^{th} percentile), income share of the middle 20^{th} percentile, and the poverty rate (the proportion of the nation's population that falls below the poverty line). In addition, as noted in the introduction we consider the country's wealth Gini coefficient in place of the income inequality measure as another check on robustness. We again use the time average of each variable in the cross-sectional regression. Table 4 reports these values and data sources.

Our prior view is that the extent to which households face binding credit constraints plays an important role in driving both the boom and bust after a consumer credit shock, and that inequality and the extent to which credit constraints bind are linked. We develop a more formal model of this mechanism in the following section, but here generally describe the implications of our prior for the cross-sectional regression. We would expect countries with a high degree of income inequality – and therefore high Gini coefficients – to have a larger number of households in the low-income tails of the distribution and thus to be more credit constrained than those countries with less income inequality. Thus, credit supply shocks are more likely to increase the burden of binding credit constraints in more unequal economies and therefore to elicit a larger consumption response. Likewise, we would expect lower financial development to be associated with a greater burden of binding credit constraints; thus, in financially less-developed economies household spending will exhibit a relatively large response to a credit shock compared to countries with higher financial development and a lower degree of binding credit constraints.

This argument implies that consumption booms and busts due to credit shocks will be large in countries with relatively low financial development and high income inequality. Consider a positive shock to domestic household credit supply in two countries that differ only according to income inequality and financial development. In the short run, consumption in both economies expands in response to the shock because credit constraints bind at least for some households; however, all else the same it will rise more in the low development/high inequality economy because the credit loosening affects a larger number of individuals. In terms of our cross-sectional regression model, a negative value for β_1 and a positive value for β_2 for short-run horizons would be consistent with this story. As the effects of the positive shock unwind, perhaps because of excess lending and other mechanisms described by Mian, Sufi, and Verner (2017), the expansionary phase makes way for the contractionary phase and consumption falls. We would again expect this bust to be larger for the low development/high inequality countries. Because this contraction happens over the medium- to long-run, we would expect to see positive β_1 estimates and negative β_2 estimates over those longer horizons.

This pattern is precisely what we find in the data, as reported in Table 5 for the baseline VAR results with respect to household credit shocks of both unit and standard deviation magnitudes. For the impact, four-quarter and short-run maximum effects, our estimate of β_1 is negative and of β_2 is positive, both of which are statistically significant according to the reported p-values. The absolute magnitude of the effect is, however, larger for unit-scaled shocks compared to standard deviation-scaled shocks. For the unit shocks in the period after impact, the coefficient estimate implies that a standard deviation increase in the financial development index of 0.1525 reduces the semi-elasticity of consumption by 53 basis points, which is almost one-half of the the cross-country standard deviation of the semi-elasticity of 120 basis points. A standard deviation increase in inequality leads to a short-run increase of 49 basis points in c_{q2}, also economically important. Note as well that adjusted R^2s are over 0.40 in the early horizons, which means that these two variables alone explain almost half the cross-country variation in the impulse responses at the short-run horizons. For unit shocks these signs reverse at longer horizons: β_1 is significantly positive after eight quarters, while β_2 becomes negative but not statistically significant. When we look at the cumulative consumption responses over horizons 1 to 12, β_2 is estimated to be 0.41, which is large and statistically significant, whereas it is -0.25 (though not statistically different from zero) for horizons 12-24, which is consistent with our priors. The final two rows of the table set y_i to be the cumulative response over a short-run period less the cumulative response over the medium- to long-run horizon. The idea here is to measure variation in the extent of the boom and bust in terms of how far the response falls from the short run to the long run (the amplitude of the cycle). We again find a statistically significant negative effect of financial development – less developed countries have bigger bust in the consumption response – and a positive effect of inequality – more inequality leads to a larger bust. This particular feature of the data has not been documented before, but it is consistent with other findings such as those of Alter, Feng, and Valckx (2018, Figure 7, p. 44) which shows that countries in which credit participation for low income households is relatively high suffer less from negative credit shocks than countries with low participation rates.

Table 6 checks the robustness of the estimates of β_2 to alternative inequality measures. For the four alternative measures of income inequality, the results are consistent with the baseline case – more income inequality leads to greater consumption responses over short horizons. For the high-inequality dummy, the Kuznets ratio and the poverty measure, this result is reflected in positive β_2 estimates in the first three rows; for the income share of the middle income group, the result is consistent with negative estimates since a higher middle income share the lower the inequality. Model fit is also similar to the baseline. The final columns report the results for wealth inequality. The coefficient estimates exhibit a similar pattern to those of the inequality measures. However, the estimates are generally smaller and less important than their income inequality counterparts, they have less explanatory power, and the p-values are higher and more often insignificant, indicating greater sampling error uncertainty. Thus, while our main results are robust to using wealth inequality, the preliminary inference here is that income inequality is the more prominent feature of the data for the issues at hand.

We have relegated to the online appendix our final set of robustness checks. We find that our results are robust to adding other control variables to account for potential omitted variable bias not accounted for by the financial development index. Those variables include real per capita GDP, the share of population between 20 and 40 years of age to control for the share of credit constrained households, and the nation's current account balance-to-GDP ratio to capture the role of international capital flows; Table A1 in the online appendix shows the data and Table A2 the results for the VAR response functions for all inequality measures. Our findings also do not significantly change when we replace the financial development index with its specific components, individually (Table A3). Finally, using the local projections responses instead of those constructed from the VAR models causes no significant change in our inference, either for baseline model (Table A4) or with additional controls (Table A5).

3 Theory

3.1 Overview

In the previous section we documented a significant and robust relationship between income inequality and the sensitivity of the response of aggregate consumption to household credit shocks, making at least a *prima facie* case for causality. In this section we develop and simulate a simple dynamic model to quantify the link between inequality and aggregate consumption's response to household debt shocks. Our modest objective is to illustrate quantitatively one potential mechanism that can explain this link; we do not attempt to construct a complete general equilibrium model, leaving that more ambitious goal for future research.

We work with a model of a small open-economy with incomplete financial markets. Our notation is for a single country, but we assume the same structure holds for all countries. There are three groups of infinitely-lived households: low-income earners with population share ω_l, middle-income earners with population share ω_m, and high-income earners with population share $\omega_h = 1 - \omega_l - \omega_m$. The economy's output is exogenous and given by an autoregressive stochastic process

$$y_t = (1 - \rho_y)\overline{y} + \rho_y y_{t-1} + \varepsilon_{y,t} \tag{2}$$

where $\epsilon_{y,t}$ is white noise and a bar above a variable denotes its steady-state value.[6] The shares of total income received by low-, middle-, and high-income earners are z_l, z_m, and $z_h = 1 - z_l - z_m$ respectively. Throughout the analysis we assume that population shares of the three groups remain constant over time. All domestic households are net borrowers; the source of domestic borrowing comes from lenders in international capital markets.

Credit constraints drive the link between inequality and spending sensitivity in our model. We assume that international lenders set an exogenous income threshold above which borrowers can borrow without any limits. Below this threshold, however, lenders impose quantity constraints based on expected income. The distinction between income groups lies in the expected burden of the credit constraints. We assume that low earners have anticipated income that never exceeds the threshold so they always face binding constraints, while high earners always have sufficient anticipated income to avoid binding constraints. On the other hand, we assume that middle-income earners have income levels that span the lending threshold. As this group's income level increases, relative to high-income earners, and average income

[6]Kumhof, Ranciere, and Winant (2015) in a related context also assume that aggregate income is exogenous.

rises above the lending threshold, a smaller share of the overall population faces binding credit constraints and consumption becomes less sensitive to credit shocks. At the same time, the rise in income share of middle earners lowers income inequality and thus the Gini coefficient.

3.2 Households and equilibrium

High-income earners maximize the expected lifetime utility function

$$E_0 \sum_{t=0}^{\infty} \beta_h^t \left(\frac{c_{h,t}^{1-\sigma}}{1-\sigma} \right), \tag{3}$$

where $\beta_h \in (0, 1)$ is the discount factor, $c_{h,t}$ is consumption, and σ is the risk-aversion parameter for high-earner households. This income group can borrow and lend without constraints, but faces a small convex financial intermediation or adjustment cost when borrowing at levels that are different from the steady-state. The budget constraint of high-income earners is thus

$$c_{h,t} + R_{t-1} b_{h,t-1} + \frac{\psi}{2}(b_{h,t} - \bar{b}_h)^2 = b_{h,t} + z_h y_t, \tag{4}$$

which holds for all periods in the planning horizon, and where $b_{h,t}$ denotes high-income household debt at time t and ψ is an adjustment cost parameter. R_{t-1} is the gross interest rate on debt that matures at time t and is taken to be exogenous and equal to the stochastic process for the world real interest rate. High-income earners maximize equation (3) with respect to (4), generating the optimality condition

$$\frac{c_{h,t+1}}{c_{h,t}} [1 - \psi(b_{h,t} - \bar{b}_h)] = \beta_h R_t \tag{5}$$

Low-income earners' utility from consumption, $c_{l,t}$, takes the same functional form as high-income earners but they are more impatient and have a lower discount factor, $\beta_l < \beta_h$.[7]

[7]Impatience is a common assumption in the literature to obtain an equilibrium in which some agents are credit constrained (Iacoviello, 2005). Frederick, Loewenstein, and O'donoghue (2002) summarize the empir-

They face the intertemporal budget constraint

$$c_{l,t} + R_{t-1} b_{l,t-1} = b_{l,t} + z_l y_t. \tag{6}$$

Low-income households also face a quantity constraint on their ability to borrow because their income is less than the lending threshold set in international capital markets; they are therefore less credit-worthy than top-tier income households. Their credit constraint is such that the total value of debt cannot exceed a time-varying fraction of expected income in the next period. As in Ludvigson (1999), we tie borrowing to expected future income because income is assumed by lenders to be associated with the borrower's financial health and ability to service the debt. The credit constraint of low-income earners takes the form

$$b_{l,t} \leq (1-\theta)\mu_t z_l E_t(y_{t+1}) + \theta b_{l,t-1}. \tag{7}$$

where $0 \leq \theta \leq 1$ measures the degree of inertia in the borrowing limit, which allows us to generate persistence in cycles. As $\theta \to 0$ the constraint takes the usual form and μ_t can be interpreted as the maximum loan-to-income ratio required by lenders. This specification is similar to the borrowing constraint used in Guerrieri and Iacoviello (2017), which includes a persistence term to reflect the slow adjustment of borrowing to house price changes. When calibrating the model we assume $\beta^l < 1/\bar{R}$, which guarantees that the credit constraint is binding in and around the steady state.

We assume μ_t follows the stochastic process

$$\mu_t = \bar{\mu} \exp(\tilde{\mu}_t) \tag{8}$$

$$\tilde{\mu}_t = \rho_\mu \tilde{\mu}_{t-1} + \varepsilon_{\mu,t}. \tag{9}$$

Low-income earners are households for whom $\bar{\mu} > 0$ always takes a finite value. A positive

ical evidence for discount rate heterogeneity across different types of households and Becker and Mulligan (1997) provide theoretical support for the hypothesis that the rich tend to be more patient.

shock to $\epsilon_{\mu,t}$ can be interpreted as an unanticipated but persistent (depending on the value of the ρ_μ) loosening of the supply of credit. The variance of this shock is σ_μ^2.

Middle-income earners have identical preferences to high- or low-income earners. However, as noted above these earners have income that can either exceed or fall below the lending threshold set by international capital markets. We make this assumption operational by allowing the credit constraint for this sector to be state-dependent. In particular, we assume that the budget and credit constraints facing middle earners are

$$c_{mt} + R_{t-1}b_{m,t-1} + \frac{\psi(z_m)}{2}(b_{m,t} - \bar{b}_m)^2 = b_{m,t} + y_t z_m \tag{10}$$

$$b_{m,t} \leq (1-\theta)\mu_m(z_m)z_m E_t(y_{t+1}) + \theta b_{m,t-1} \tag{11}$$

$$\psi(z_m) = \begin{cases} \psi & z_m \geq \phi \\ 0 & z_m < \phi \end{cases} \tag{12}$$

$$\mu_m(z_m) = \begin{cases} \infty & z_m \geq \phi \\ \mu_t & z_m < \phi. \end{cases} \tag{13}$$

We take ϕ to be the income share that reflects the level of income consistent with the lending threshold. As income share z_m rises above ϕ, the middle-earner group becomes more like the high-income group and pays adjustment costs but faces no constraint (we can think of the 'loan-to-income' ratio as going to infinity in this case). At the same time, since the middle group's income share rises and its population share is fixed, the economy's Gini coefficient necessarily falls. For small z_m, there is no adjustment cost for borrowing, but middle earners now face the same borrowing constraint as low income households. Our simulation experiment below considers such a 'regime-shift' for middle earners.

To fix ideas about this experiment, consider a simple numerical example. Suppose that there are 1,000 households in the economy, with respective population, per-capita income and income shares:

i	n_i	y_i/n_i	z_i
l	20%	\$10,000	1.2%
m	70%	\$100,000	40.7%
h	10%	\$1,000,000	58.1%

Assuming per-capita income is the same for individuals within each group, the implied Gini coefficient is 55.5.[8] Now, increase income in the low-income sector by 20% and in the middle-income sector by 50%, holding income constant for the rich. The income share of middle earners rises to 50.6%, that of high earners falls to 48.2%, and the Gini coefficient falls to 47.5%. If the lending threshold for individual borrowers is \$125,000, then the increased level of income and income share of the middle-income group lead, in our model, to a reduction in the population share of credit-constrained households from 90% to 10%.

In equilibrium, all households maximize their respective lifetime utilities with respect to the relevant credit and budget constraints, the market for borrowing and lending clears, and the market clearing condition for goods holds. The market-clearing conditions are

$$B_t = (1 - \omega_m - \omega_l) b_{h,t} + \omega_m b_{m,t} + \omega_l b_{l,t} \tag{14}$$

$$y_t = \omega_l c_{l,t} + \omega_m c_{m,t} + (1 - \omega_m - \omega_l) c_{h,t} + AC_t + NX_t \tag{15}$$

$$AC_t = \frac{\psi}{2}(b_{h,t} - \bar{b}_h)^2 + \frac{\psi(z_m)}{2}(b_{m,t} - \bar{b}_m)^2 \tag{16}$$

$$NX_t = R_t B_{t-1} - B_t \tag{17}$$

3.3 Model simulation

We are interested in the model's prediction for how aggregate consumption changes in the face of credit supply shocks, here given by $\epsilon_{\mu,t}$. We do not calibrate the model, *per se*, but assume plausible values for all parameters and then compute the dynamic response of consumption to an identical credit shock for alternative values of the income share of the

[8] If we assume that income share is a continuous function of population share the Gini coefficient can be written as a function of income and population shares: $Gini = 1 - 2[.5z_l\omega_l + (z_l + .5z_m)\omega_m + (1 - .5z_h)\omega_h]$.

middle-earner group. In the baseline model, which we refer to as the low-inequality regime, middle-earner income share is set at $z_m = 0.45$, which we assume is sufficiently high to eliminate the credit constraint for this group. Alternatively, in the high-inequality regime we set $z_m = 0.35$ and assume that the credit constraint binds. We then solve the model given all parameter values and compute the impulse responses of consumption to credit shocks for each case.

Table 7 reports the parameter values for the alternative parameterizations, along with the implied Gini coefficients. Note that as the middle-earner income share falls from 0.45 to 0.35, the Gini coefficient rises from 0.28 to 0.36. An increase in the Gini coefficient of 0.08 is slightly larger than the standard deviation of 0.068 we observe in the data. Given the population shares, in the low-inequality regime 20% of the population is credit constrained; in the high-inequality regime that magnitude rises to 80%.

Figure 5 shows the model's impulse response functions for consumption under the two cases, along with the (exogenous) response of the loan-to-income ratio μ_t (red curve), which is the same for both scenarios. The shock in this case is a one-time positive impulse to $\epsilon_{\mu,t}$ equal to its assumed standard deviation of 0.02. The shock yields a persistent, but not permanent, effect on μ_t. The general dynamic patterns for consumption are similar to what is seen in the data – a persistent response and a short-run increase in consumption with a declining effect over time.[9] Also evident is the variation in magnitudes given the change in income shares. For the low-inequality country, consumption exhibits an immediate 0.04% rise which essentially falls to zero after four quarters. On the other hand the high-inequality country experiences a 0.18% increase in consumption on impact – more than four times the low-inequality effect – as well as a larger decline after one year.

Although we do not perform a precise calibration exercise, the model simulations accord well with the data. And while we cannot make direct comparisons with Figure 2, note that the countries with large Gini coefficients – Argentina, Brazil, Mexico, Russia and Turkey

[9]We interpret period 1 in the model to the second quarter horizon in the data, given the Cholesky ordering in the VAR.

(each of these countries has a Gini coefficient over .40, well above the average of .33) – have estimated impulse response functions similar to the model's high-inequality country, while the Czech Republic, Netherlands, and other countries with lower Gini coefficients behave more like the low-inequality country.

3.4 Discussion

Our simple theoretical model shows that countries with higher income inequality experience larger consumption responses to household credit shocks. The key assumption underlying our theory is that income inequality leads to a higher share of credit constrained households. Note that while our study proposes this novel link between income distribution and the share of credit constrained households, the model abstracts from the amplification mechanisms prior literature has focused on when studying the role of credit constraints for the link between household debt and business cycles. Our aim in this sub-section is to tie our theoretical model to existing studies on household debt and business cycles. To this end, we discuss recent theoretical models based on credit constraints and household heterogeneity.

Heterogeneity across agents is a common feature of the general equilibrium models that study the role of financial frictions for aggregate fluctuations. In these models, population is composed of two types of households: impatient constrained borrowers and patient unconstrained lenders. Borrowers have a higher propensity to spend than lenders, therefore demand shocks that affect impatient households act as a powerful amplification mechanism. An extensive literature builds on this assumption to study the effects of real and financial shocks on business cycles. For example, in Iacoviello (2005) collateral constraints amplify the effects of housing demand and monetary policy shocks. Bahadir and Gumus (2016) show that shocks to credit constrained households' credit limits generate expansions in output and consumption. Alpanda and Zubairy (2016) study the effect of fiscal policy shocks in the existence of collateral constraints and housing. Eggertsson and Krugman (2012) and Korinek and Simsek (2016) focus on the differences in marginal propensity to consume for patient and impatient households to study the deleveraging effects of constrained borrowers. In all these models, the effect of shocks that generate model dynamics are amplified due to the existence of credit constrained households.

Precautionary saving and borrowing behavior is another channel through which the share of credit constrained households matters for business cycles. Guerrieri and Lorenzoni (2017) studies the effects of a credit crunch on consumer spending in a heterogeneous-agent incomplete-market model. In their model, an unexpected permanent tightening in consumers' borrowing capacity leads constrained consumers to deleverage and unconstrained households increase their precautionary savings. In a similar vein, Druedahl and Jorgensen (2018) argue that current debt can potentially soften a household's borrowing constraint in future periods, and thus provides extra liquidity. In these models, the share of credit constrained households also plays an important role for the model dynamics.

To summarize, the share of credit constrained households determines the strength of the mechanisms studied in the heterogenous agent models. Our paper contributes to this literature by arguing that income distribution is a possible determinant of the share of credit constrained households, and therefore is likely to affect the response of the economy to real and financial shocks.

4 Conclusion

The aim of this paper has been to examine the link between income inequality and the 'household demand channel' of credit supply shocks. We document such a link in the data for a sample of developed and developing countries. Time series models for each country suggest that credit shocks temporarily raise aggregate consumption (which is consistent with the extant literature), while cross-country regressions using the time-series estimates show that the short-run rise and long-run decline of spending is larger for countries with a more unequal distribution of income than other countries. We also provide a theoretical model that associates inequality with the extent of binding credit constraints to illustrate a potential mechanism that can drive the empirical results. Simulations show that the model generates heterogenous consumption responses, as they vary with income equality, similar to those estimated from the data.

The empirical link that we have documented here between income inequality and the nature of household credit shocks is an important finding. However, we see this paper as taking only the first steps toward a more complete analysis. Most importantly, we have not provided a tight link between the data and the theoretical model and our model leaves out important general equilibrium effects. Understanding such effects is needed to better understand the relevance of the model's economic mechanisms and the implications for policy. Future work in this area should consider these effects, as well as why wealth inequality seems to be less important for our story of the household demand channel than income inequality.

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Table 1: Consumption and debt ratios: sample means

No.	*Country*	*Begin*	*End*	$ln(cons)$	$\frac{hhdebt}{gdp}$	$\frac{firmdebt}{gdp}$
1	Argentina	1994:1	2017:1	11.01	0.048	0.242
2	Australia	1991:1	2017:2	25.82	0.848	0.691
3	Austria	1996:1	2017:3	6.54	0.487	0.845
4	Belgium	1995:1	2017:3	6.57	0.464	1.187
5	Brazil	1997:1	2017:3	10.49	0.161	0.409
6	Canada	1990:1	2017:3	7.58	0.716	0.901
7	Czech Republic	1995:4	2017:3	8.38	0.191	0.586
8	Denmark	1995:1	2017:3	7.82	1.074	0.894
9	Finland	1990:1	2017:3	5.32	0.461	0.977
10	France	1990:1	2017:1	7.81	0.418	1.032
11	Germany	1991:1	2017:3	8.15	0.611	0.547
12	Greece	1995:1	2017:3	6.10	0.374	0.497
13	Hungary	1995:1	2016:4	9.97	0.197	0.659
14	Israel	1992:3	2017:3	6.93	0.375	0.743
15	Italy	1995:1	2016:4	7.75	0.319	0.672
16	Japan	1994:1	2016:4	13.47	0.643	1.148
17	Korea	1991:1	2017:3	13.79	0.631	0.933
18	Mexico	1995:1	2017:3	20.94	0.117	0.199
19	Netherlands	1995:1	2017:3	7.59	0.993	1.204
20	New Zealand	1998:2	2017:3	8.12	0.798	0.859
21	Norway	1990:1	2017:1	7.67	0.692	1.177
22	Poland	1996:1	2017:3	7.73	0.204	0.353
23	Portugal	1995:1	2017:3	5.81	0.696	1.035
24	Russia	1998:1	2017:3	9.45	0.080	0.354
25	Singapore	1991:1	2017:2	5.45	0.413	0.863
26	Spain	1995:1	2017:3	6.88	0.613	0.947
27	Sweden	1990:1	2017:2	8.12	0.607	1.172
28	Switzerland	1999:4	2017:1	7.12	1.118	0.931
29	Thailand	1993:1	2017:3	8.92	0.495	1.175
30	Turkey	1990:1	2017:3	7.29	0.073	0.301
31	UK	1990:1	2016:2	7.79	0.742	0.780
32	US	1990:1	2017:3	9.04	0.768	0.634
	mean			9.11	0.513	0.780
	st. dev.			4.20	0.289	0.297

Statistics reported are sample means over the given time range for each country. μ and σ are cross-sectional mean and standard deviation.

Table 2: Consumption response to household credit shocks from VAR

No.	*Country*	c_{max}		c_{q2}		c_{q4}		c_{q8}	
		unit	std. dev	unit	std. dev	unit	std. dev	unit	std. dev
1	Argentina	6.822	0.995	6.236	0.910	5.267	0.769	-0.438	-0.064
2	Australia	0.541	0.366	0.144	0.094	0.262	0.171	0.431	0.280
3	Austria	0.594	0.284	0.190	0.091	0.594	0.284	0.500	0.239
4	Belgium	0.001	0.000	-0.085	-0.039	-0.022	-0.010	-0.072	-0.034
5	Brazil	1.642	0.677	1.176	0.485	1.406	0.580	1.420	0.586
6	Canada	0.008	0.004	-0.079	-0.041	0.008	0.004	-0.248	-0.129
7	Czech Republic	0.314	0.159	0.287	0.145	0.216	0.109	-0.104	-0.052
8	Denmark	0.271	0.276	0.101	0.104	0.244	0.249	0.221	0.226
9	Finland	0.341	0.116	0.165	0.056	0.341	0.116	-0.205	-0.070
10	France	0.432	0.121	-0.234	-0.065	0.423	0.118	0.244	0.068
11	Germany	0.285	0.107	-0.182	-0.067	0.066	0.024	0.205	0.075
12	Greece	1.665	0.522	0.750	0.235	1.074	0.337	1.566	0.491
13	Hungary	0.345	0.227	0.345	0.227	-0.130	-0.086	-0.507	-0.334
14	Israel	0.236	0.108	-0.305	-0.138	-0.608	-0.276	-0.244	-0.111
15	Italy	2.439	0.445	0.081	0.015	1.553	0.284	2.193	0.400
16	Japan	0.113	0.098	0.008	0.004	-0.201	-0.109	-0.026	-0.014
17	Korea	0.000	0.000	-0.364	-0.280	-0.985	-0.757	-1.753	-1.348
18	Mexico	2.561	0.438	1.994	0.341	2.475	0.423	0.077	0.013
19	Netherlands	0.232	0.170	-0.025	-0.019	0.177	0.130	0.190	0.140
20	New Zealand	1.064	0.408	0.482	0.185	0.963	0.369	0.859	0.330
21	Norway	0.438	0.252	0.314	0.181	0.438	0.252	0.133	0.077
22	Poland	0.000	0.000	-0.215	-0.094	-0.125	-0.054	-0.560	-0.244
23	Portugal	1.852	0.816	0.369	0.163	1.219	0.537	1.827	0.805
24	Russia	2.269	0.489	2.172	0.468	2.253	0.486	-2.482	-0.535
25	Singapore	0.354	0.170	-0.399	-0.191	0.206	0.099	0.324	0.156
26	Spain	1.066	0.568	0.211	0.112	0.776	0.413	1.049	0.559
27	Sweden	0.939	0.283	0.216	0.065	0.808	0.243	0.758	0.228
28	Switzerland	0.155	0.088	-0.322	-0.143	-0.290	-0.129	-0.069	-0.031
29	Thailand	1.042	0.520	0.593	0.296	1.042	0.520	0.343	0.171
30	Turkey	2.189	0.564	2.189	0.564	0.581	0.150	-0.122	-0.032
31	UK	0.829	0.266	0.006	0.002	0.725	0.232	0.763	0.244
32	US	0.608	0.295	0.199	0.096	0.398	0.193	0.608	0.295
	mean	0.989	0.307	0.500	0.117	0.661	0.177	0.215	0.075
	st. dev.	1.295	0.242	1.227	0.238	1.102	0.283	0.894	0.372

c_{max} indicates peak consumption response over 12 quarters; c_{qj} indicates consumption response at quarter j. Columns indicate unit shock or standard deviation shock.

Table 3: Financial development index and components

No.	Country	FD	FI_d	FI_e	FI_a	FM_d	FM_e	FM_a
1	Argentina	0.337	0.152	0.526	0.241	0.090	0.283	0.562
2	Australia	0.768	0.766	0.739	0.719	0.609	0.528	0.588
3	Austria	0.628	0.602	0.777	0.572	0.276	0.361	0.659
4	Belgium	0.534	0.589	0.803	0.452	0.434	0.263	0.232
5	Brazil	0.462	0.372	0.354	0.535	0.213	0.548	0.303
6	Canada	0.748	0.778	0.744	0.723	0.670	0.449	0.452
7	Czech Republic	0.354	0.200	0.546	0.327	0.100	0.330	0.043
8	Denmark	0.647	0.760	0.778	0.726	0.369	0.397	0.299
9	Finland	0.561	0.577	0.812	0.234	0.482	0.522	0.271
10	France	0.671	0.655	0.794	0.667	0.520	0.567	0.208
11	Germany	0.717	0.652	0.757	0.705	0.464	0.828	0.458
12	Greece	0.513	0.248	0.738	0.667	0.281	0.399	0.394
13	Hungary	0.421	0.238	0.626	0.315	0.140	0.448	0.477
14	Israel	0.517	0.522	0.638	0.507	0.255	0.409	0.328
15	Italy	0.680	0.460	0.712	0.804	0.365	0.642	0.439
16	Japan	0.733	0.663	0.843	0.880	0.506	0.720	0.381
17	Korea	0.735	0.592	0.713	0.604	0.462	0.919	0.519
18	Mexico	0.349	0.136	0.608	0.245	0.172	0.418	0.420
19	Netherlands	0.725	0.872	0.823	0.566	0.617	0.609	0.309
20	New Zealand	0.545	0.482	0.723	0.584	0.275	0.182	0.575
21	Norway	0.620	0.444	0.772	0.327	0.425	0.575	0.702
22	Poland	0.394	0.224	0.672	0.406	0.100	0.577	0.403
23	Portugal	0.613	0.428	0.802	0.959	0.334	0.461	0.178
24	Russia	0.358	0.082	0.319	0.368	0.172	0.296	0.324
25	Singapore	0.680	0.712	0.797	0.314	0.684	0.467	0.665
26	Spain	0.741	0.500	0.792	0.896	0.517	0.666	0.437
27	Sweden	0.658	0.698	0.727	0.388	0.636	0.541	0.391
28	Switzerland	0.896	0.849	0.774	0.803	0.814	0.771	0.845
29	Thailand	0.535	0.377	0.797	0.274	0.419	0.727	0.320
30	Turkey	0.394	0.100	0.426	0.317	0.178	0.673	0.334
31	UK	0.798	0.816	0.808	0.782	0.730	0.538	0.519
32	US	0.806	0.717	0.503	0.826	0.762	0.845	0.471
	mean	0.598	0.508	0.695	0.554	0.408	0.530	0.422
	st. dev.	0.153	0.233	0.137	0.218	0.207	0.177	0.164

Source: Svirydzenka (2016). FD is the overall financial development index, which comprises specific components for financial institutions and markets: FI_d, FI_e, & FI_a indicate depth, efficiency, and access of financial institutions. FM_d, FM_e, & FM_a indicate depth, efficiency, and access of financial markets.

Table 4: Measures of inequality

No.	Country	$Gini_Y$	Kuznets	third 20%	poverty	$Gini_W$
1	Argentina	0.433	0.127	0.139	0.182	0.773
2	Australia	0.320	0.057	0.163	0.012	0.657
3	Austria	0.272	0.047	0.174	0.007	0.737
4	Belgium	0.256	0.043	0.177	0.004	0.645
5	Brazil	0.497	0.210	0.112	0.361	0.815
6	Canada	0.305	0.056	0.170	0.007	0.722
7	Czech Republic	0.246	0.038	0.177	0.007	0.720
8	Denmark	0.238	0.038	0.176	0.005	0.903
9	Finland	0.243	0.040	0.174	0.002	0.688
10	France	0.287	0.050	0.167	0.002	0.725
11	Germany	0.273	0.046	0.170	0.003	0.762
12	Greece	0.336	0.063	0.170	0.035	0.681
13	Hungary	0.280	0.046	0.176	0.028	0.614
14	Israel	0.348	0.084	0.159	0.037	0.772
15	Italy	0.328	0.063	0.170	0.022	0.649
16	Japan	0.302	0.054	0.173	0.01	0.616
17	Korea	0.292	0.054	0.174	0.013	0.700
18	Mexico	0.466	0.139	0.124	0.399	0.769
19	Netherlands	0.261	0.043	0.174	0.003	0.743
20	New Zealand	0.326	-	-	-	0.720
21	Norway	0.246	0.039	0.176	0.003	0.768
22	Poland	0.306	0.058	0.169	0.048	0.729
23	Portugal	0.341	0.066	0.158	0.028	0.709
24	Russia	0.402	0.077	0.149	0.150	0.873
25	Singapore	0.390	-	-	-	0.753
26	Spain	0.327	0.064	0.171	0.024	0.647
27	Sweden	0.243	0.042	0.179	0.010	0.820
28	Switzerland	0.295	0.052	0.167	0.001	0.788
29	Thailand	0.429	0.073	0.144	0.295	0.803
30	Turkey	0.425	0.082	0.151	0.206	0.817
31	UK	0.338	0.057	0.166	0.007	0.698
32	US	0.365	0.088	0.156	0.017	0.843
	μ	0.325	0.067	0.164	0.064	0.739
	σ	0.068	0.036	0.016	0.109	0.071
	ρ		0.877	-0.943	0.877	0.305

Source: Data on the after-tax income gini coefficient ($Gini_Y$) are taken from Solt (2016). Data on the Kuznets ratio, third income quintile, and poverty are from World Bank Database. Data on wealth Gini ($Gini_W$) are from various issues of the Credit Suisse Global Wealth Databook. Values are time averages from 1990-2017 for all income inequality measures, and from 2010 to 2017 for the wealth Gini coefficient. ρ is the correlation coefficient with respect to the after-tax income Gini coefficient.

Table 5: Cross-sectional regression: baseline results

y	β_0		β_1		β_2		R^2	
	unit	std. dev	unit	std. dev	unit	std. dev	unit	std. dev
c_{max}	-0.005	-0.002	-0.025	-0.002	0.092	0.021	0.429	0.424
	(0.577)	(0.236)	(0.064)	(0.274)	(0.002)	(0.000)		
c_{q2}	0.003	0.001	-0.035	-0.008	0.072	0.014	0.483	0.561
	(0.763)	(0.542)	(0.006)	(0.000)	(0.008)	(0.001)		
c_{q4}	-0.004	-0.002	-0.022	-0.003	0.073	0.017	0.403	0.260
	(0.606)	(0.409)	(0.051)	(0.188)	(0.002)	(0.000)		
c_{q8}	-0.018	-0.007	0.020	0.006	0.025	0.013	0.102	0.073
	(0.009)	(0.008)	(0.037)	(0.098)	(0.110)	(0.026)		
c_{q12}	-0.025	-0.010	0.043	0.012	-0.010	0.006	0.170	0.129
	(0.048)	(0.007)	(0.042)	(0.025)	(0.779)	(0.469)		
c_{q16}	-0.025	-0.010	0.047	0.013	-0.024	0.002	0.195	0.171
	(0.066)	(0.009)	(0.041)	(0.014)	(0.518)	(0.836)		
c_{q20}	-0.021	-0.009	0.039	0.011	-0.023	0.001	0.214	0.192
	(0.046)	(0.007)	(0.032)	(0.008)	(0.463)	(0.916)		
c_{q24}	-0.016	-0.007	0.025	0.008	-0.014	0.001	0.196	0.157
	(0.033)	(0.011)	(0.036)	(0.015)	(0.490)	(0.860)		
$\sum_{q1}^{q12} c$	-0.150	-0.059	0.080	0.035	0.405	0.146	0.107	0.081
	(0.009)	(0.018)	(0.367)	(0.286)	(0.002)	(0.006)		
$\sum_{q12}^{q24} c$	-0.290	-0.115	0.522	0.147	-0.259	0.029	0.201	0.175
	(0.049)	(0.006)	(0.036)	(0.012)	(0.532)	(0.798)		
$\sum_{q1}^{q24} c$	-0.415	-0.165	0.559	0.169	0.156	0.168	0.126	0.108
	(0.019)	(0.006)	(0.062)	(0.035)	(0.744)	(0.248)		
$(\bar{c})_{q1}^{q12} - (\bar{c})_{q12}^{q24}$	0.010	0.004	-0.033	-0.008	0.054	0.010	0.324	0.306
	(0.276)	(0.064)	(0.022)	(0.005)	(0.040)	(0.134)		
$(\bar{c})_{q1}^{q8} - (\bar{c})_{q16}^{q24}$	0.014	0.006	-0.046	-0.011	0.071	0.012	0.338	0.321
	(0.242)	(0.043)	(0.017)	(0.003)	(0.042)	(0.146)		

Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \epsilon_i$, where y_i is a summary measure of each country's dynamic response of consumption to household credit shocks in country i; z_{i1} is the financial development index and z_{i2} is the Gini index. c_{max} indicates the peak response over 12 quarters. c_{qj}, $\sum_{qj}^{qk} c$, and $\left[(\bar{c})_{qj}^{qk} - (\bar{c})_{ql}^{qm}\right]$ indicate respectively response at quarter j, cumulative response over quarters j to k, and average response over quarters j to k less l to m. Columns indicate unit shock or standard deviation shock. p-values based on robust standard errors in parentheses.

Table 6: Cross-sectional regression: robustness to inequality measures

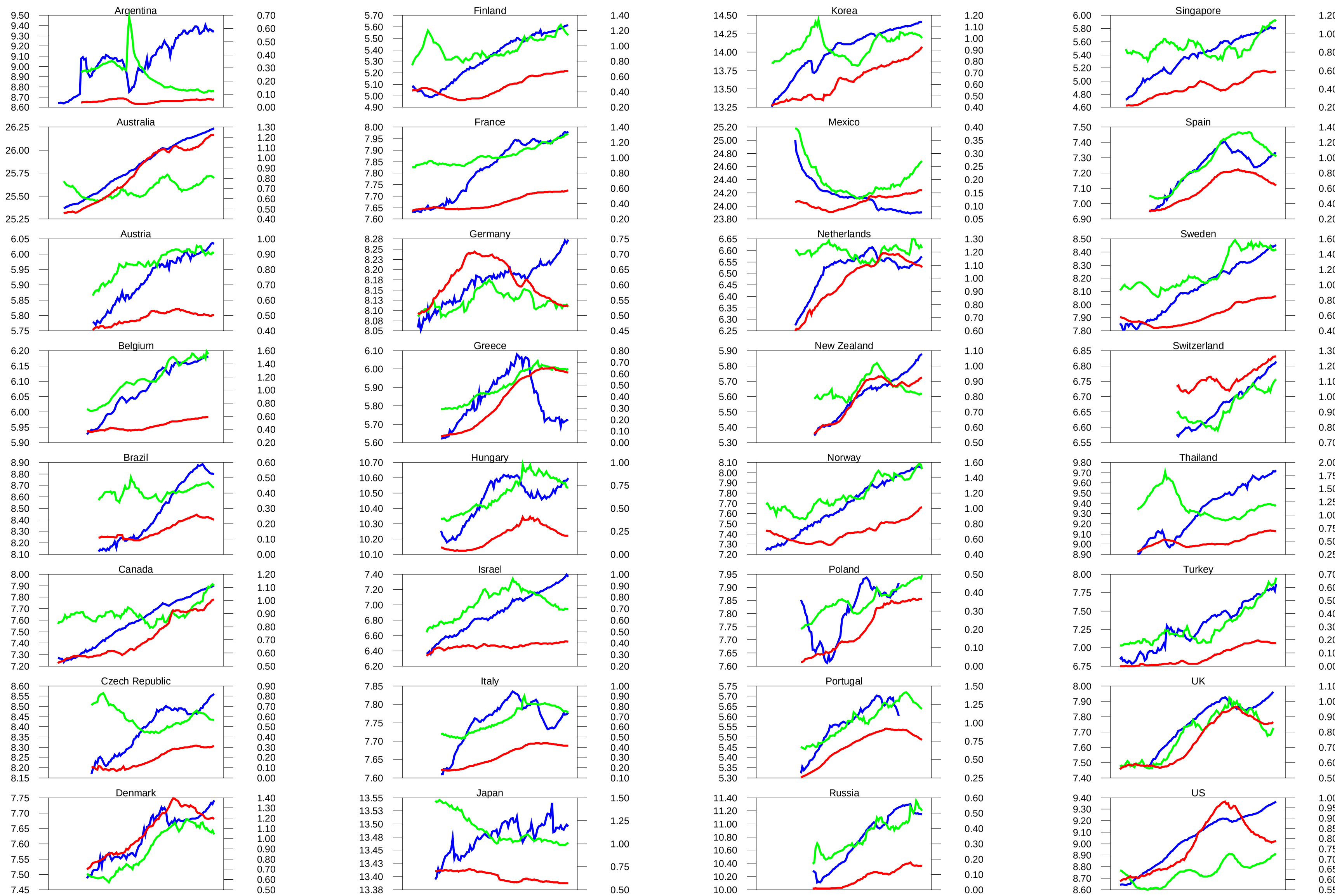
y	$Gini_Y$ (dummy)		Kuznets		third 20%		poverty		$Gini_W$	
	β_2	R^2	β_2	R^2	β_2	R^2	β_2	R^2	β_2	R^2
A. Unit Shock										
c_{max}	0.018	0.417	0.162	0.382	-0.376	0.388	0.045	0.315	0.020	0.237
	(0.036)		(0.104)		(0.021)		(0.015)		(0.334)	
c_{q2}	0.017	0.540	0.131	0.460	-0.314	0.473	0.039	0.420	0.032	0.382
	(0.033)		(0.132)		(0.032)		(0.022)		(0.021)	
c_{q4}	0.014	0.383	0.136	0.378	-0.338	0.410	0.043	0.340	0.025	0.253
	(0.052)		(0.070)		(0.007)		(0.001)		(0.156)	
c_{q20}	0.007	0.230	0.038	0.220	0.039	0.210	0.000	0.208	-0.047	0.257
	(0.487)		(0.444)		(0.782)		(0.982)		(0.298)	
c_{q24}	0.007	0.232	0.027	0.196	0.005	0.188	0.001	0.188	-0.021	0.210
	(0.349)		(0.338)		(0.958)		(0.929)		(0.491)	
$\sum_{q1}^{q12} c$	0.102	0.167	1.058	0.188	-1.962	0.124	0.269	0.092	-0.110	0.010
	(0.010)		(0.000)		(0.000)		(0.002)		(0.607)	
$\sum_{q12}^{q24} c$	0.097	0.218	0.576	0.207	0.400	0.199	0.016	0.198	-0.667	0.250
	(0.491)		(0.407)		(0.839)		(0.953)		(0.285)	
$(\bar{c})_{q1}^{q12} - (\bar{c})_{q12}^{q24}$	0.001	0.257	0.044	0.267	-0.194	0.299	0.021	0.276	0.042	0.308
	(0.905)		(0.444)		(0.139)		(0.222)		(0.246)	
$(\bar{c})_{q1}^{q8} - (\bar{c})_{q16}^{q24}$	0.002	0.272	0.059	0.282	-0.258	0.314	0.028	0.290	0.056	0.323
	(0.861)		(0.450)		(0.146)		(0.222)		(0.229)	
B. Standard Deviation Shock										
c_{max}	0.004	0.355	0.036	0.358	-0.088	0.389	0.011	0.303	0.005	0.159
	(0.000)		(0.001)		(0.000)		(0.001)		(0.231)	
c_{q2}	0.003	0.630	0.027	0.556	-0.067	0.581	0.010	0.548	0.007	0.466
	(0.000)		(0.002)		(0.000)		(0.002)		(0.012)	
c_{q4}	0.003	0.236	0.031	0.237	-0.086	0.293	0.012	0.251	0.009	0.170
	(0.007)		(0.000)		(0.000)		(0.000)		(0.042)	
c_{q20}	0.002	0.220	0.025	0.241	-0.026	0.206	0.001	0.198	-0.008	0.216
	(0.487)		(0.003)		(0.476)		(0.890)		(0.413)	
c_{q24}	0.002	0.198	0.018	0.197	-0.027	0.175	0.001	0.159	-0.003	0.162
	(0.403)		(0.006)		(0.306)		(0.846)		0.658	
$\sum_{q1}^{q12} c$	0.029	0.078	0.355	0.124	-0.775	0.113	0.097	0.070	0.026	0.010
	(0.017)		(0.000)		(0.001)		(0.018)		(0.709)	
$\sum_{q12}^{q24} c$	0.028	0.202	0.357	0.227	-0.400	0.191	0.025	0.181	-0.111	0.196
	(0.452)		(0.003)		(0.408)		(0.802)		(0.435)	
$(\bar{c})_{q1}^{q12} - (\bar{c})_{q12}^{q24}$	0.000	0.263	0.002	0.263	-0.034	0.287	0.006	0.294	0.011	0.324
	(0.913)		(0.762)		(0.232)		(0.341)		(0.150)	
$(\bar{c})_{q1}^{q8} - (\bar{c})_{q16}^{q24}$	0.000	0.282	0.002	0.280	-0.042	0.302	0.008	0.310	0.014	0.342
	(0.897)		(0.803)		(0.252)		(0.345)		(0.147)	

For definitions, see Table 4 and notes to Table 5.

Table 7: Parameter values for low- and high-inequality regimes. Values below the dashed line are determined by values above the dashed line.

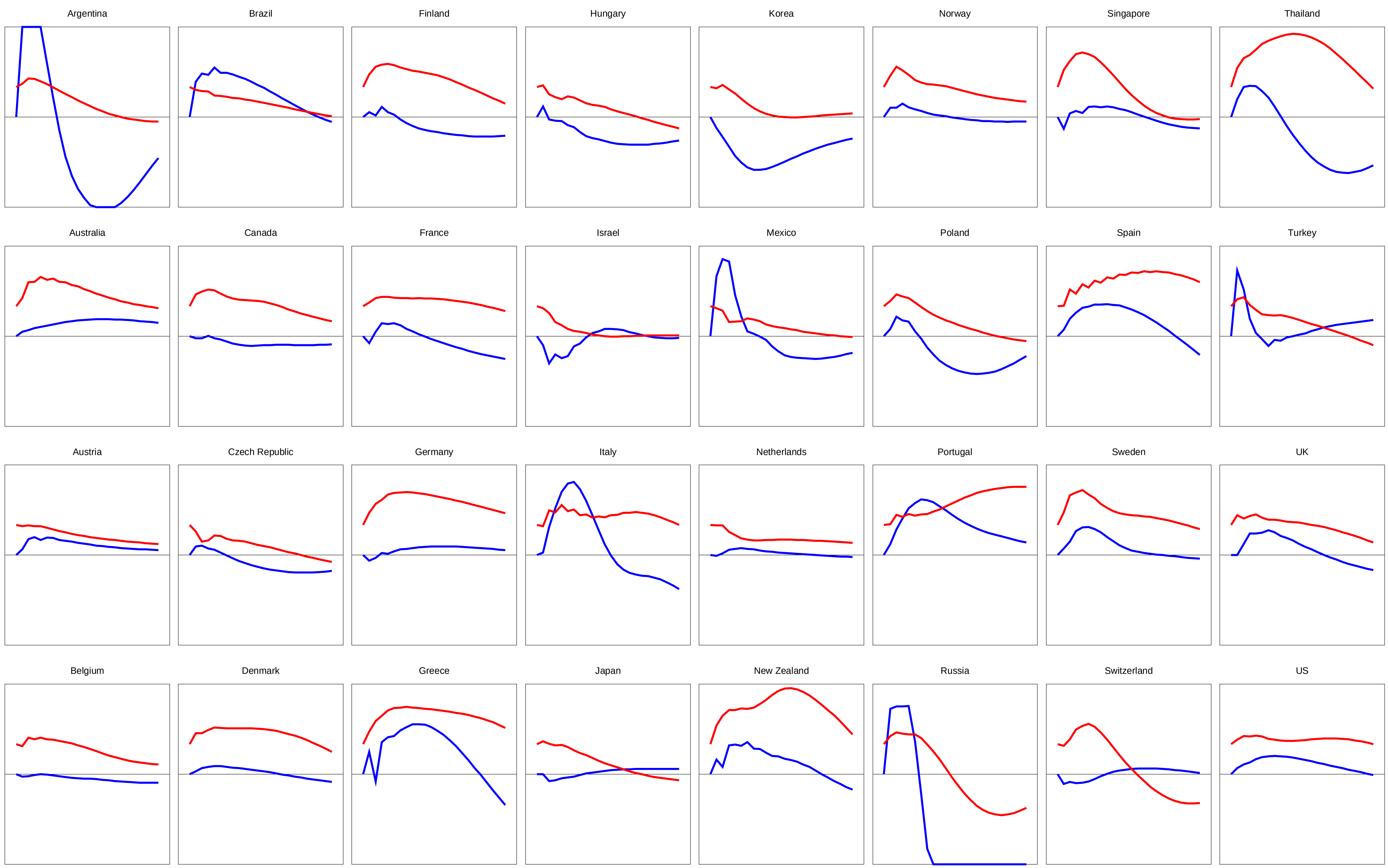
Parameter	Inequality		Description
	Low	High	
β_l	0.96	0.96	Discount factor: low earners
β_m	0.99	0.96	Discount factor: middle earners
β_h	0.99	0.99	Discount factor: high earners
σ	1.00	1.00	Relative risk aversion
ω_l	0.20	0.20	Population share: low earners
ω_m	0.60	0.60	Population share: middle earners
$\bar{R}$	1.01	1.01	Real interest rate
θ	0.60	0.60	Inertia in borrowing limit
ψ	0.006	0.006	Adjustment cost parameter
ρ_m	0.90	0.90	Persistence of credit shock
σ_m	0.02	0.02	Standard deviation of credit shock
$\bar{\mu}_l$	0.50	0.50	Loan-to-income: low earners
$\bar{\mu}_m$	–	0.50	Loan-to-income: middle earners
$\bar{\mu}_h$	0.50	0.50	Loan-to-income: high earners
$\bar{b}_m$	0.50	–	Steady-state borrowing: middle earners
$\bar{b}_h$	0.50	0.50	Steady-state borrowing: high earners
z_l	0.10	0.10	Income share: low earners
z_m	**0.45**	**0.35**	Income share: middle earners
z_h	**0.45**	**0.55**	Income share: high earners
$\bar{b}_l/\bar{b}$	0.05	0.08	Borrowing share: low earners
$\bar{b}_m/\bar{b}$	0.68	0.53	Borrowing share: middle earners
B_t/y_t	0.46	0.33	Aggregate borrowing to output
Gini	0.28	0.36	Gini coefficient: income distribution

Figure 1: Consumption and debt ratios



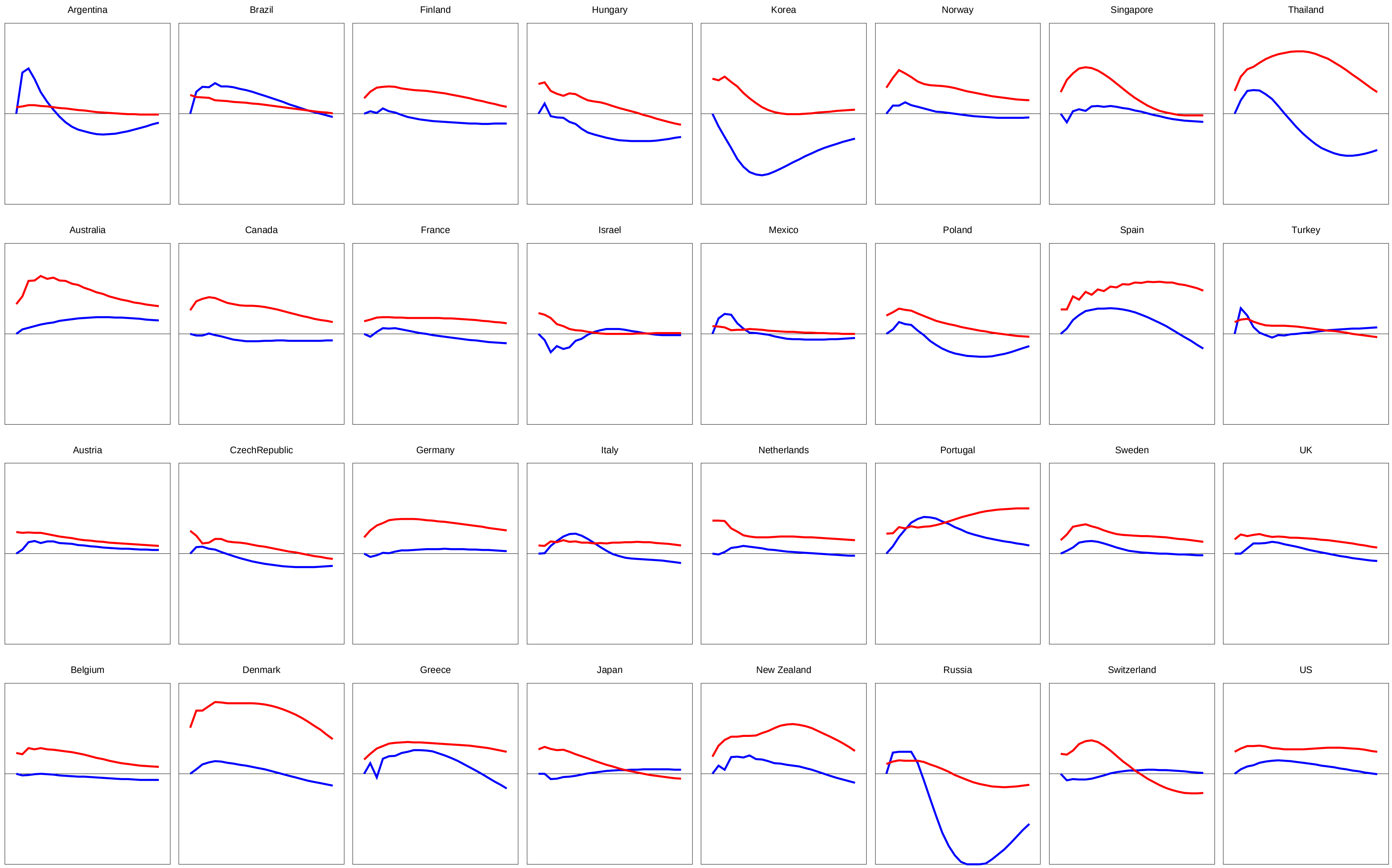
Log consumption: blue, left scale; $\frac{hhdebt}{gdp}$: red, right scale; $\frac{firmdebt}{gdp}$: green, right scale. Maximum data range is 1990 to 2017.

Figure 2: Impulse responses for log consumption to a unit household credit shock from baseline VAR



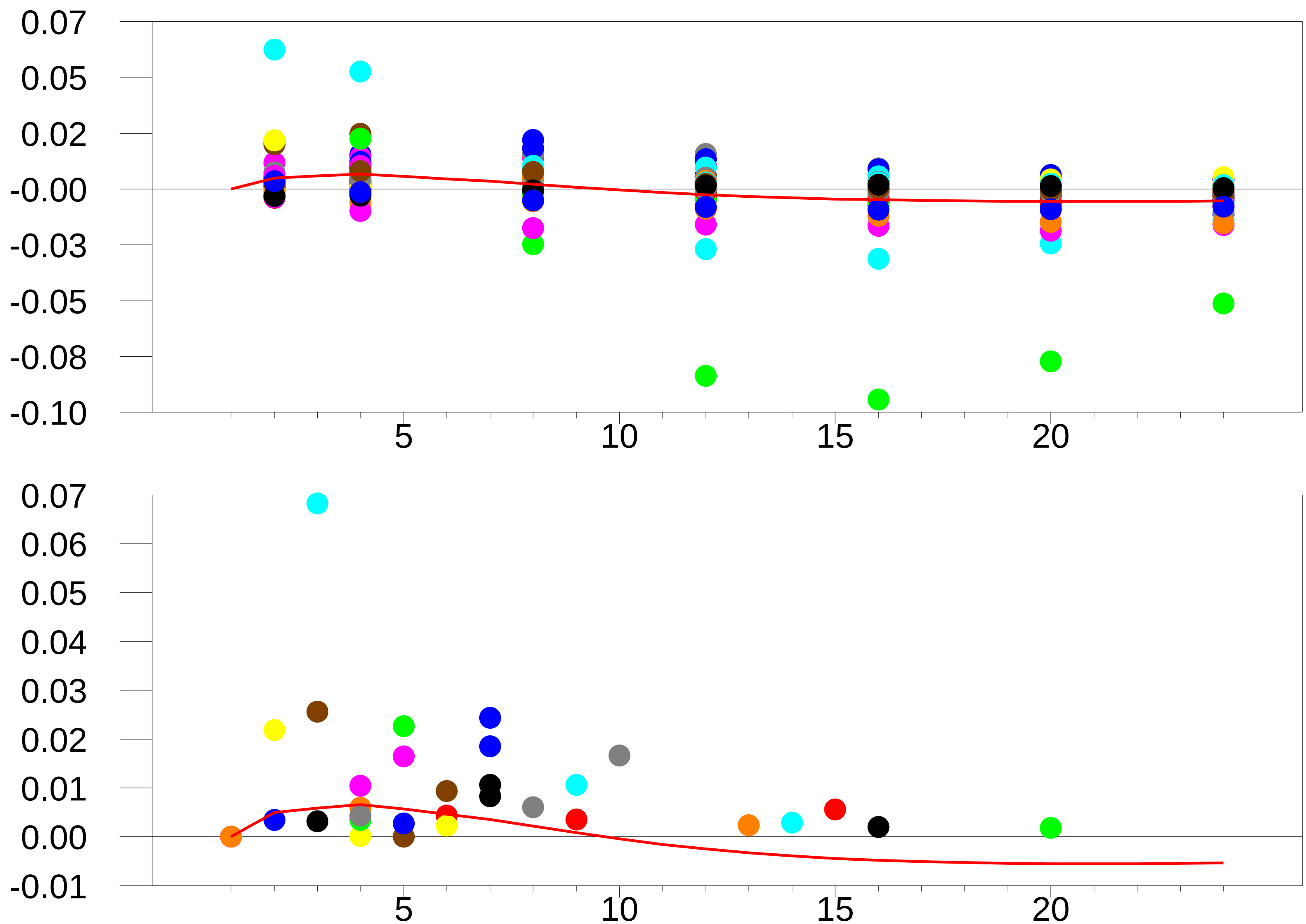
Log consumption response, blue; household debt ratio response, red. Forecast horizons on horizontal axis range from 1 to 24.

Figure 3: Impulse responses for log consumption to a std. deviation household credit shock from baseline VAR



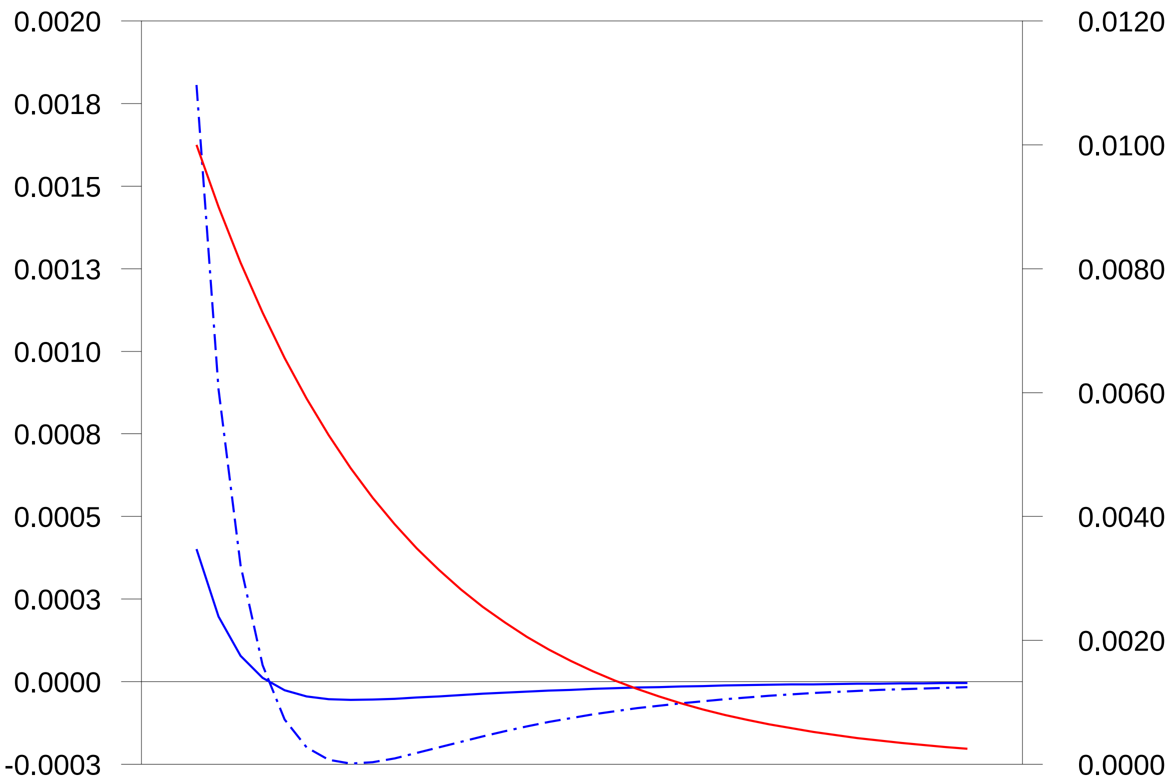
Log consumption response, blue; household debt ratio response, red. Forecast horizons on horizontal axis range from 1 to 24.

Figure 4: Summary consumption responses from recursive VAR



Notes: The dots in the top panel plot the the dynamic responses of consumption to unit household credit shock. The dots in the bottom panel plot each country's peak consumption response. The solid red curve in both panels plots the cross-sectional mean response.

Figure 5: Theoretical impulse responses of consumption to a household credit shock



The solid red line (right-hand scale) plots the response of the loan-to-income ratio, μ; the dashed and solid blue lines (left-hand scale) plot the responses of consumption to the shock in high and low income countries respectively.

5 Online Appendix (not for publication): Household Debt, Consumption and Inequality

Time-series model identification and supplemental tables and figures

We estimate structural impulse response functions in two ways: standard inversion of a VAR model and directly through local projections. In general, for n-dimensional vector process Y_t, the set of impulse response functions for forecast horizon k is given by

$$IRF(k) = E(Y_{t+k}|Y_t + dY_t, Y_{t-1}, Y_{t-2}, \cdots) - E(Y_{t+k}|Y_t, Y_{t-1}, Y_{t-2}, \cdots), \tag{18}$$

where dY_t is taken to be an unexpected innovation or shock. $IRF(k)$ is an $n \times 1$ vector that measures the change in the conditional projection of Y_{t+k} given an impulse in the vector Y_t, and is independent of the data generating process. In our application,

$$Y_t = \begin{bmatrix} c_t \\ D_t^{fy} \\ D_t^{hy} \end{bmatrix}. \tag{19}$$

Under the assumption that the data are generated by a linear vector autoregression (assuming a first order model without loss of generality)

$$Y_t = \phi Y_{t-1} + \epsilon_t, \tag{20}$$

where ϵ_t is a vector of reduced-form forecast errors with covariance matrix $E\epsilon_t\epsilon_t' = \Sigma$. Since $dY_t = d\epsilon_t$,

$$IRF(k) = \phi^k d\epsilon_t. \tag{21}$$

We assume the reduced form errors are linear combinations of orthogonal structural shocks, $\epsilon_t = D_0\Omega^{\frac{1}{2}}u_t$ where D_0 is an $n \times n$ matrix of structural parameters with ones along the diagonal and $Eu_tu_t' = \Omega$, a diagonal matrix. This implies that the conditional expectation of Y_{t+k} is updated in response to structural shocks according to

$$IRF(k) = \phi^k D_0\Omega^{\frac{1}{2}} du_t. \tag{22}$$

This expression can be calculated by estimating ϕ from the VAR in (20) using standard techniques, assuming that D_0 is lower triangular, and identifying $D_0\Omega^{\frac{1}{2}}$ as the Cholesky factor of Σ. The recursive restrictions on D_0 are consistent with our structural interpretation in the text. As we note in the text, we report dynamic responses to unit-valued structural shocks; i.e., the responses are based on D_0 rather than $D_0\Omega^{\frac{1}{2}}$.

Under the local projections approach, we make no assumptions about the data generating process but rely on a more general formulation of linear projection:

$$E(Y_{t+k}|Y_t, \cdots, Y_{t-p}) = B_kY_t + \gamma_1 Y_{t-1} + \cdots + \gamma_{p_k} Y_{t-p_k} \tag{23}$$

which implies

$$IRF(k) = B_k dY_t = B_k D_0 \Omega^{\frac{1}{2}} du_t \tag{24}$$

where we have made the same mapping from structure to reduced form as above. The only difference between the VAR and local projections approach to estimating structural impulse response functions is how the weighting matrices ϕ_k and B_k are estimated. As we've assumed that D_0 is lower triangular, the local projections estimates of the response of consumption to household credit shocks are the coefficients on the household credit to GDP ratio in the consumption local projections equations.

Table A1: Measures of additional controls

No.	Country	$ln(gdp)$	curr. acct.	age
1	Argentina	9.684	-0.006	0.711
2	Australia	10.519	-0.043	0.732
3	Austria	10.585	0.025	0.724
4	Belgium	10.526	0.014	0.690
5	Brazil	9.436	-0.016	0.794
6	Canada	10.495	-0.012	0.731
7	Czech Republic	10.098	-0.024	0.735
8	Denmark	10.642	0.036	0.679
9	Finland	10.475	0.019	0.658
10	France	10.454	0.002	0.679
11	Germany	10.544	0.031	0.688
12	Greece	10.137	-0.053	0.729
13	Hungary	9.916	-0.037	0.713
14	Israel	10.206	0.004	0.697
15	Italy	10.470	0.000	0.693
16	Japan	10.453	0.028	0.661
17	Korea	10.086	0.020	0.833
18	Mexico	9.666	-0.022	0.770
19	Netherlands	10.640	0.056	0.705
20	New Zealand	10.301	-0.037	0.710
21	Norway	10.965	0.091	0.701
22	Poland	9.839	-0.034	0.740
23	Portugal	10.129	-0.049	0.712
24	Russia	9.856	0.056	0.758
25	Singapore	10.999	0.171	0.822
26	Spain	10.301	-0.026	0.759
27	Sweden	10.559	0.038	0.663
28	Switzerland	10.860	0.088	0.720
29	Thailand	9.327	0.013	0.810
30	Turkey	9.693	-0.029	0.769
31	UK	10.440	-0.026	0.694
32	US	10.739	-0.028	0.710
	μ	10.282	0.008	0.725
	σ	0.421	0.047	0.045

Source: World Development Indicators (WDI), World Bank Database. μ and σ are the cross-sectional mean and standard deviation.

Table A2: Cross-sectional regression: robustness to other control variables

$y = c_{max}$	$Gini_Y$		$Gini_Y$ (dummy)		Kuznets		third 20%		poverty		$Gini_W$	
	β_2	R^2	β_2	R^2	β_2	R^2	β_2	R^2	β_2	R^2	β_2	R^2
A. Unit Shock												
$z_{i3}= ln(gdp)$	0.104	0.433	0.021	0.422	0.169	0.381	-0.434	0.392	0.046	0.313	0.020	0.279
	(0.011)		(0.053)		(0.133)		(0.025)		(0.031)		(0.298)	
$z_{i3}=$ curr. acct.	0.092	0.430	0.018	0.419	0.163	0.380	-0.375	0.386	0.044	0.317	0.029	0.253
	(0.002)		(0.039)		(0.118)		(0.026)		(0.016)		(0.165)	
$z_{i3}=$ age	0.138	0.530	0.022	0.455	0.191	0.406	-0.475	0.426	0.064	0.349	0.020	0.237
	(0.002)		(0.024)		(0.091)		(0.019)		(0.007)		(0.340)	
B. Standard Deviation Shock												
$z_{i3}= ln(gdp)$	0.019	0.426	0.003	0.362	0.030	0.372	-0.081	0.392	0.009	0.315	0.005	0.286
	(0.002)		(0.060)		(0.017)		(0.009)		(0.165)		(0.140)	
$z_{i3}=$ curr. acct.	0.020	0.464	0.004	0.401	0.034	0.381	-0.084	0.419	0.011	0.357	0.009	0.253
	(0.000)		(0.001)		(0.002)		(0.000)		(0.002)		(0.018)	
$z_{i3}=$ age	0.026	0.471	0.004	0.359	0.037	0.358	-0.094	0.394	0.013	0.308	0.005	0.170
	(0.000)		(0.001)		(0.003)		(0.001)		(0.011)		(0.268)	

Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \beta_3 z_{i3} + \epsilon_i$, where y_i is c_{max}, z_{i1} is the financial development index, z_{i2} is the inequality index and z_{i3} is the control variable. p-values based on robust standard errors in parenthesis.

Table A3: Cross-sectional regression: robustness to specific components for financial institutions and markets

$y = c_{max}$	$Gini_Y$ (VAR) β_2	R^2	$Gini_Y$ (Jorda LP) β_2	R^2
A. Unit Shock				
$z_{i1}= FI_d$	0.082	0.450	0.088	0.443
	(0.007)		(0.006)	
$z_{i1}= FI_e$	0.096	0.373	0.114	0.347
	(0.005)		(0.002)	
$z_{i1}= FI_a$	0.109	0.374	0.127	0.341
	(0.001)		(0.000)	
$z_{i1}= FM_d$	0.097	0.438	0.105	0.454
	(0.002)		(0.000)	
$z_{i1}= FM_e$	0.112	0.433	0.125	0.430
	(0.001)		(0.000)	
$z_{i1}= FM_a$	0.113	0.359	0.127	0.345
	(0.003)		(0.000)	
B. Standard Deviation Shock				
$z_{i1}= FI_d$	0.018	0.456	0.020	0.231
	(0.000)		(0.093)	
$z_{i1}= FI_e$	0.022	0.407	0.026	0.206
	(0.000)		(0.013)	
$z_{i1}= FI_a$	0.023	0.415	0.028	0.265
	(0.000)		(0.003)	
$z_{i1}= FM_d$	0.020	0.452	0.020	0.278
	(0.000)		(0.038)	
$z_{i1}= FM_e$	0.022	0.452	0.025	0.242
	(0.000)		(0.012)	
$z_{i1}= FM_a$	0.023	0.412	0.025	0.239
	(0.000)		(0.009)	

Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \epsilon_i$, where y_i is c_{max}, z_{i1} is the specific component for financial institutions and markets, and z_{i2} is the gini index. FI_d, FI_e, & FI_a indicate depth, efficiency, and access of financial institutions. FM_d, FM_e, & FM_a indicate depth, efficiency, and access of financial markets. p-values based on robust standard errors in parenthesis.

Table A4: Cross-sectional regression, Jorda LP

y	$Gini_Y$ β_2	$Gini_Y$ R^2	$Gini_Y$ (dummy) β_2	$Gini_Y$ (dummy) R^2	Kuznets β_2	Kuznets R^2	third 20% β_2	third 20% R^2	poverty β_2	poverty R^2	$Gini_W$ β_2	$Gini_W$ R^2
A. Unit Shock												
c_{max}	0.101	0.417	0.015	0.331	0.209	0.430	-0.422	0.386	0.045	0.300	0.006	0.233
	(0.000)		(0.111)		(0.002)		(0.002)		(0.068)		(0.836)	
c_{q2}	0.089	0.433	0.020	0.477	0.166	0.413	-0.422	0.449	0.054	0.381	0.043	0.307
	(0.001)		(0.024)		(0.079)		(0.008)		(0.001)		(0.014)	
c_{q4}	0.049	0.168	0.001	0.030	0.089	0.145	-0.222	0.167	0.027	0.108	0.016	0.046
	(0.003)		(0.834)		(0.001)		(0.002)		(0.066)		(0.468)	
c_{q20}	-0.078	0.206	-0.023	0.254	-0.126	0.194	0.336	0.205	-0.029	0.176	-0.058	0.191
	(0.225)		(0.237)		(0.519)		(0.338)		(0.393)		(0.013)	
c_{q24}	-0.080	0.274	-0.004	0.153	-0.082	0.190	0.332	0.262	-0.047	0.239	-0.062	0.240
	(0.009)		(0.736)		(0.261)		(0.041)		(0.018)		(0.119)	
$\sum_{q1}^{q12} c$	-0.022	0.130	-0.027	0.133	0.525	0.154	-0.726	0.145	0.216	0.157	-0.326	0.154
	(0.961)		(0.817)		(0.651)		(0.761)		(0.441)		(0.215)	
$\sum_{q12}^{q24} c$	-1.045	0.242	-0.205	0.240	-1.165	0.217	3.916	0.234	-0.249	0.208	-1.032	0.251
	(0.217)		(0.407)		(0.632)		(0.406)		(0.618)		(0.035)	
$(\bar{c})_{q1}^{q12} - (\bar{c})_{q12}^{q24}$	0.079	0.299	0.014	0.266	0.133	0.267	-0.362	0.302	0.037	0.231	0.052	0.245
	(0.017)		(0.204)		(0.149)		(0.040)		(0.062)		(0.033)	
$(\bar{c})_{q1}^{q8} - (\bar{c})_{q16}^{q24}$	0.103	0.302	0.019	0.277	0.167	0.263	-0.461	0.300	0.050	0.235	0.066	0.241
	(0.015)		(0.169)		(0.173)		(0.046)		(0.049)		(0.027)	
B. Standard Deviation Shock												
c_{max}	0.022	0.221	0.003	0.143	0.054	0.294	-0.104	0.231	0.012	0.165	0.003	0.100
	(0.035)		(0.241)		(0.001)		(0.050)		(0.208)		(0.750)	
c_{q2}	0.021	0.409	0.005	0.463	0.038	0.382	-0.104	0.463	0.015	0.417	0.014	0.316
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.001)	
c_{q4}	0.018	0.130	0.001	0.029	0.036	0.142	-0.090	0.169	0.012	0.111	0.008	0.037
	(0.013)		(0.470)		(0.007)		(0.008)		(0.070)		(0.212)	
c_{q20}	-0.011	0.178	-0.004	0.242	-0.006	0.164	0.043	0.183	-0.007	0.183	-0.021	0.273
	(0.377)		(0.213)		(0.837)		(0.511)		(0.451)		(0.000)	
c_{q24}	-0.021	0.168	-0.002	0.066	-0.019	0.081	0.081	0.144	-0.015	0.168	-0.021	0.192
	(0.021)		(0.551)		(0.151)		(0.034)		(0.024)		(0.020)	
$\sum_{q1}^{q12} c$	0.071	0.084	0.013	0.082	0.372	0.168	-0.723	0.145	0.105	0.135	0.000	0.072
	(0.593)		(0.651)		(0.189)		(0.264)		(0.257)		(0.996)	
$\sum_{q12}^{q24} c$	-0.175	0.243	-0.032	0.237	-0.004	0.225	0.494	0.239	-0.057	0.233	-0.265	0.308
	(0.293)		(0.466)		(0.992)		(0.592)		(0.648)		(0.018)	
$(\bar{c})_{q1}^{q12} - (\bar{c})_{q12}^{q24}$	0.019	0.249	0.004	0.225	0.031	0.205	-0.098	0.284	0.013	0.235	0.020	0.297
	(0.007)		(0.087)		(0.008)		(0.003)		(0.029)		(0.000)	
$(\bar{c})_{q1}^{q8} - (\bar{c})_{q16}^{q24}$	0.025	0.248	0.005	0.234	0.037	0.192	-0.121	0.273	0.017	0.241	0.026	0.290
	(0.006)		(0.066)		(0.018)		(0.006)		(0.026)		(0.000)	

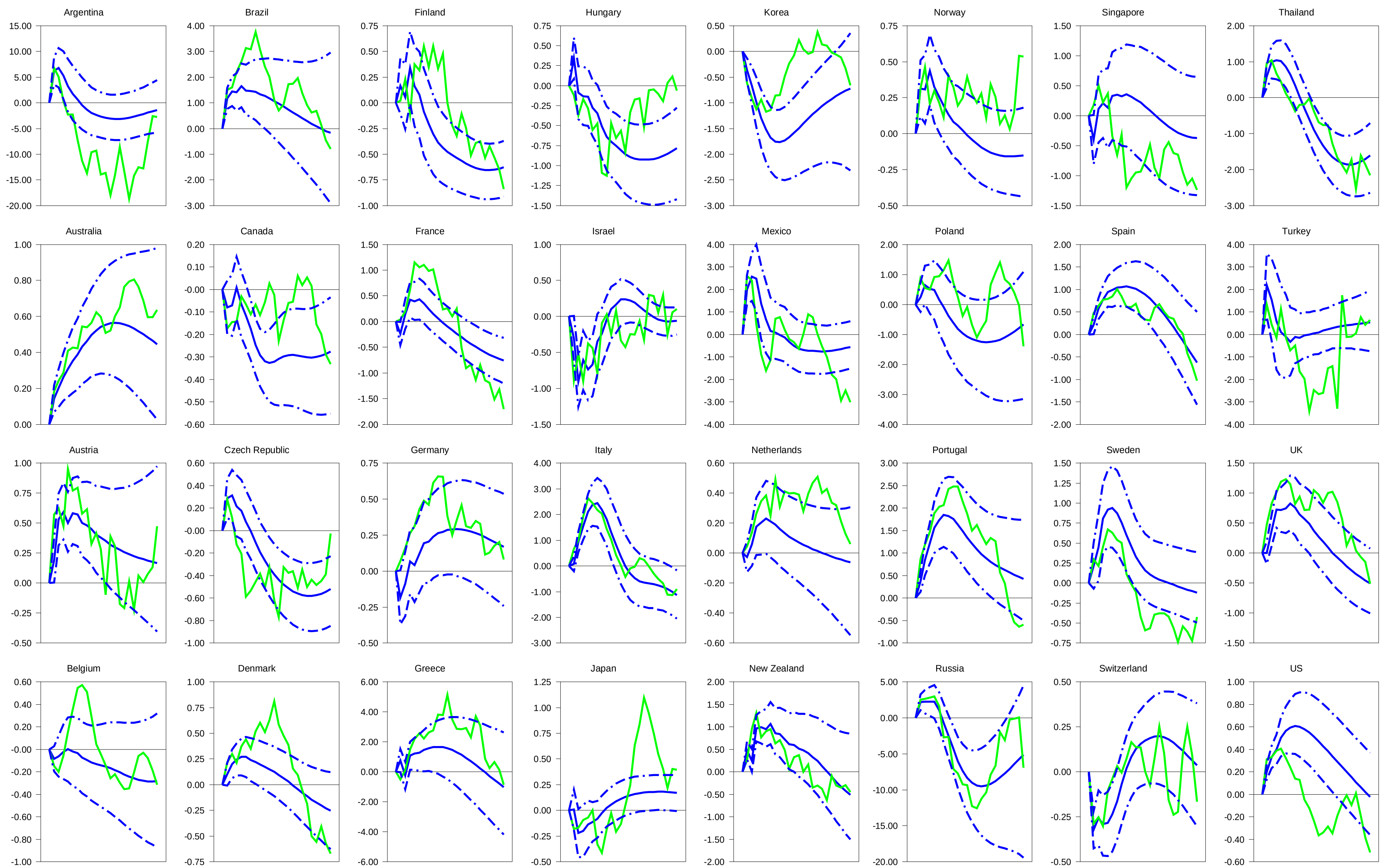
Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \epsilon_i$, where y_i is a summary measure of each country's dynamic response of consumption to household credit shocks in country i; z_{i1} is the financial development index and z_{i2} is the inequality index. c_{max} indicates the peak response over 12 quarters. c_{qj}, $\sum_{qj}^{qk} c$, and $\left[(\bar{c})_{qj}^{qk} - (\bar{c})_{ql}^{qm}\right]$ indicate respectively response at quarter j, cumulative response over quarters j to k, and average response over quarters j to k less l to m. Columns indicate unit shock or standard deviation shock. p-values based on robust standard errors in parentheses.

Table A5: Cross-sectional regression: robustness to other control variables, Jorda LP

$y = c_{max}$	$Gini_Y$		$Gini_Y$ (dummy)		Kuznets		third 20%		poverty		$Gini_W$	
	β_2	R^2	β_2	R^2	β_2	R^2	β_2	R^2	β_2	R^2	β_2	R^2
A. Unit Shock												
z_{i3}= $ln(gdp)$	0.104	0.418	0.013	0.335	0.215	0.430	-0.445	0.387	0.034	0.305	0.006	0.292
	(0.010)		(0.288)		(0.009)		(0.021)		(0.257)		(0.828)	
z_{i3}= curr. acct.	0.099	0.433	0.015	0.351	0.202	0.435	-0.406	0.397	0.045	0.324	0.020	0.264
	(0.001)		(0.125)		(0.006)		(0.009)		(0.073)		(0.475)	
z_{i3}= age	0.148	0.499	0.018	0.346	0.240	0.453	-0.515	0.414	0.061	0.319	0.006	0.233
	(0.000)		(0.090)		(0.003)		(0.004)		(0.046)		(0.841)	
B. Standard Deviation Shock												
z_{i3}= $ln(gdp)$	0.016	0.240	0.001	0.197	0.048	0.301	-0.082	0.241	0.005	0.193	0.003	0.198
	(0.123)		(0.794)		(0.011)		(0.206)		(0.653)		(0.748)	
z_{i3}= curr. acct.	0.021	0.270	0.003	0.199	0.050	0.322	-0.096	0.271	0.012	0.224	0.009	0.170
	(0.043)		(0.263)		(0.007)		(0.087)		(0.215)		(0.367)	
z_{i3}= age	0.027	0.236	0.003	0.144	0.055	0.295	-0.106	0.231	0.012	0.165	0.002	0.101
	(0.012)		(0.250)		(0.001)		(0.062)		(0.269)		(0.815)	

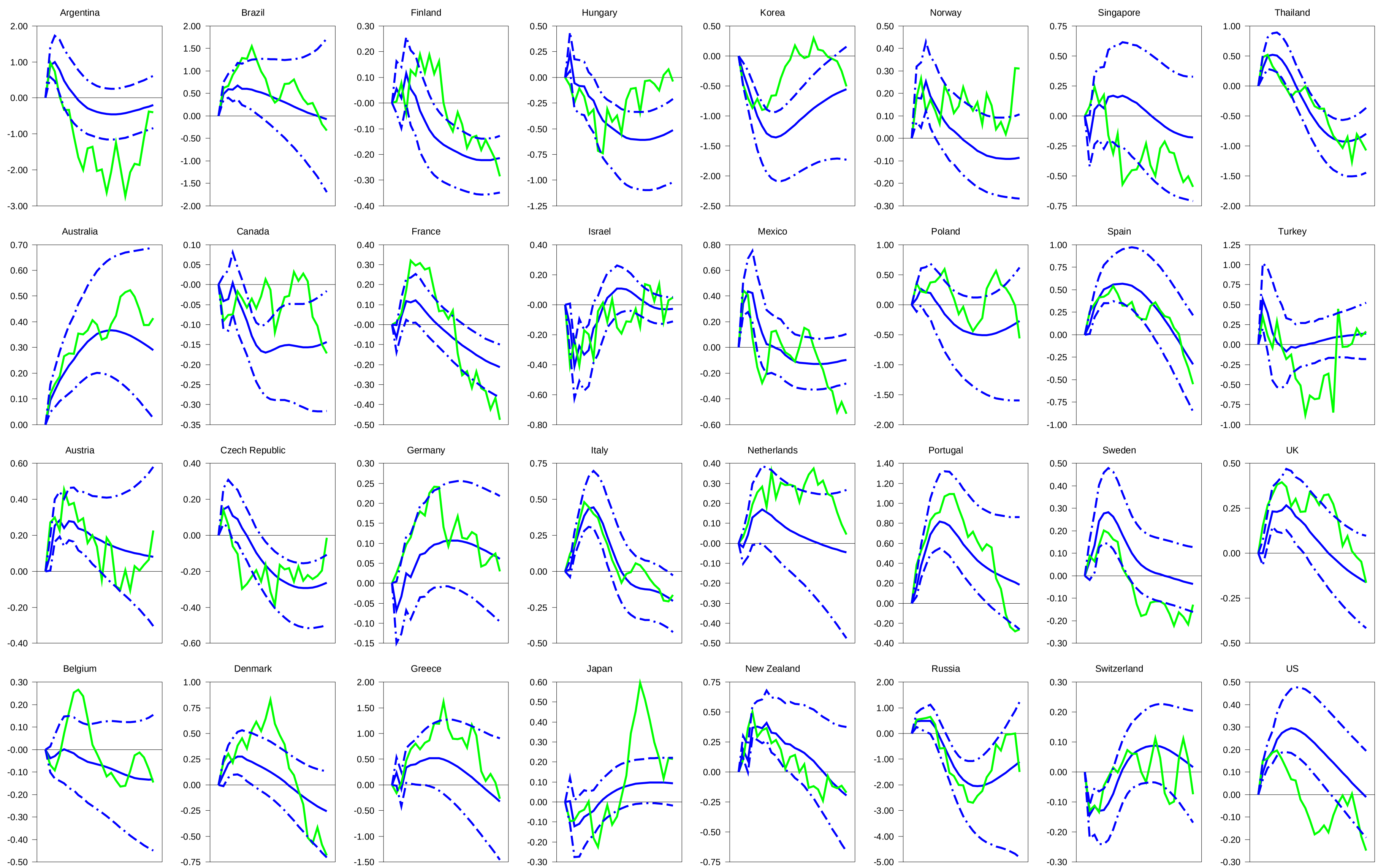
Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \beta_3 z_{i3} + \epsilon_i$, where y_i is c_{max}, z_{i1} is the financial development index, z_{i2} is the inequality index and z_{i3} is the control variable. p-values based on robust standard errors in parenthesis.

Figure A1: Impulse responses for real consumption to unit household credit shock



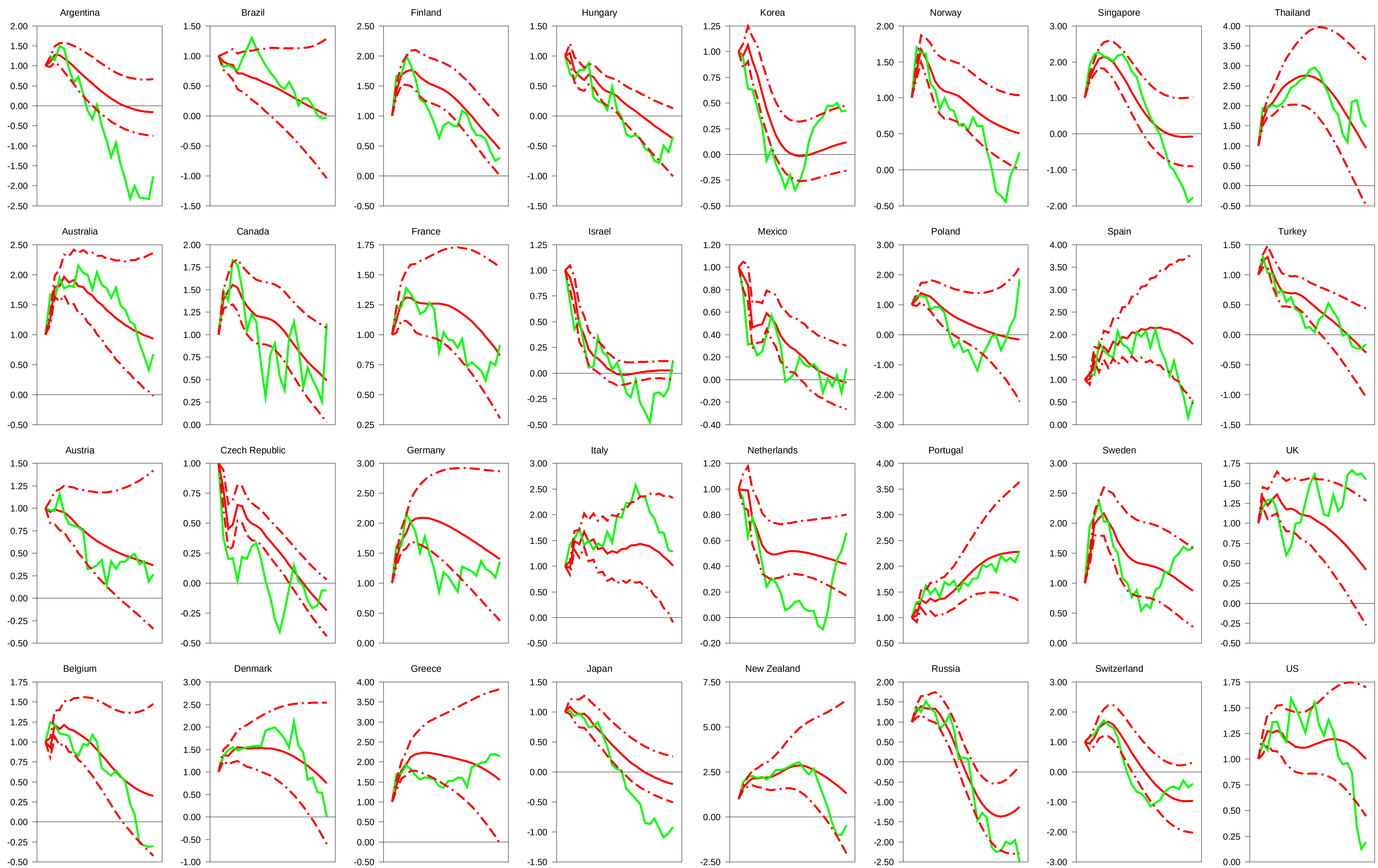
The solid blue line plots the consumption response from recursive VAR, while the solid green line from Jorda LP. The dotted blue lines plot the two std. deviation error bands. Note differences in vertical scale.

Figure A2: Impulse responses for real consumption to std. deviation household credit shock



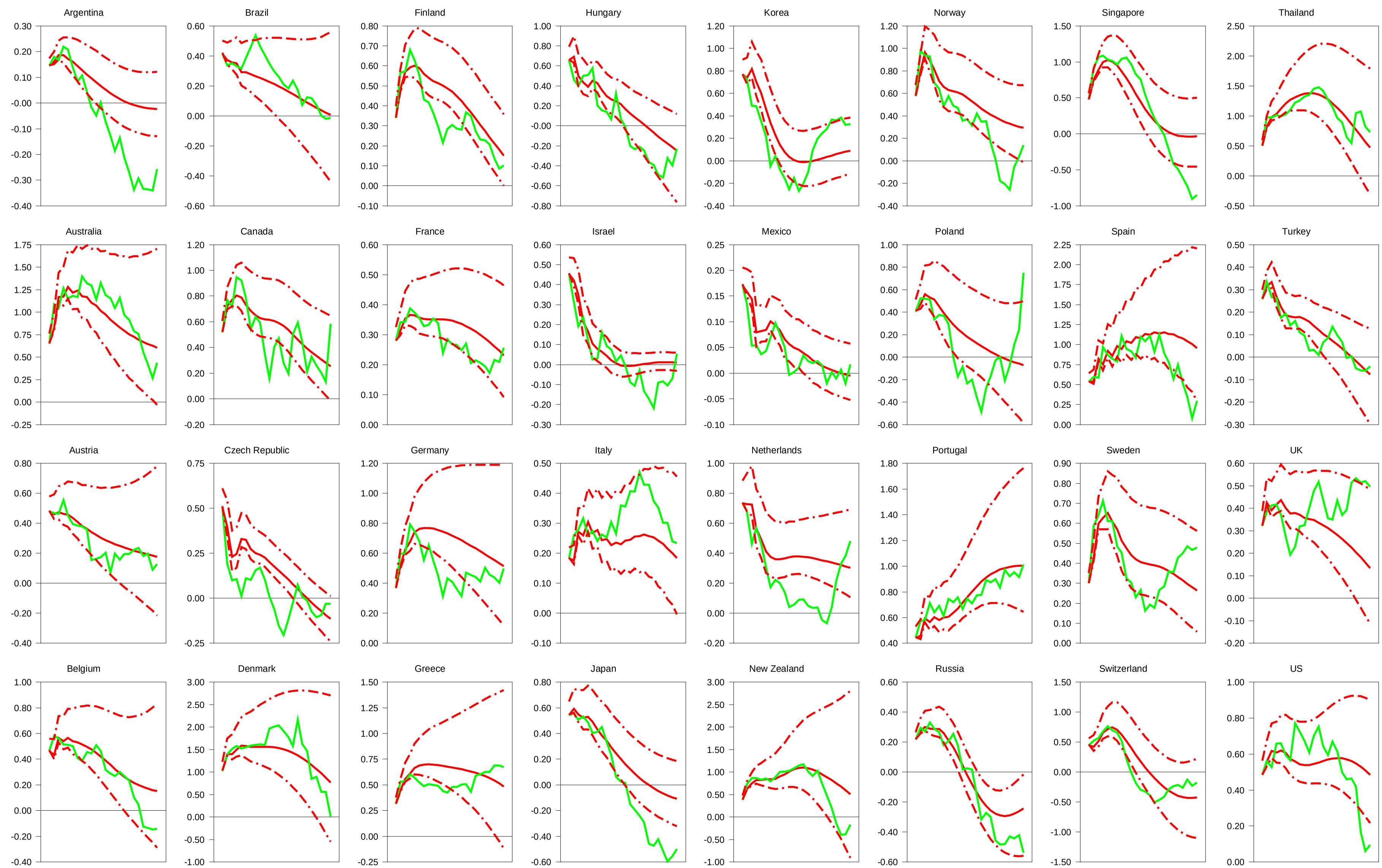
The solid blue line plots the consumption response from recursive VAR, while the solid green line from Jorda LP. The dotted blue lines plot the two std. deviation error bands.

Figure A3: Impulse responses for household debt to GDP to unit household credit shock



The solid red line plots the household debt to GDP response from recursive VAR, while the solid green line from Jorda LP. The dotted red lines plot the two std. deviation error bands.

Figure A4: Impulse responses for household debt to GDP to std. deviation household credit shock



The solid red line plots the household debt to GDP response from recursive VAR, while the solid green line from Jorda LP. The dotted red lines plot the two std. deviation error bands.