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JEL classification: E44, E47, G51

Keywords: household debt, GDP forecasting, quantile regression

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Juho Nyholm† and Ville Voutilainen‡

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1 Introduction

The relationship between household leverage and economic growth is of great interest to policymakers. In the aftermath of the 2008 global financial crisis, macroprudential regulation increased in many countries. Actions in the EU were initially taken to enhance the capital buffers of the banking sector, giving authorities power to set them countercyclically and separately enhance the buffers of systemically important banks.

More recently, the emphasis has moved to households' leverage and demand-side macroprudential tools. In most European countries, the size of new mortgages is constrained regulatory specification of collateral or other wealth requirements. *Debt-to-income* or *loan-to-income* type of constraints have been set, for example, in Ireland, the United Kingdom, Latvia, and Norway. In the Netherlands and Estonia, mortgage caps are tied to the customer's *debt-service-to-income* ratio. In Latvia, Lithuania, Norway, Sweden, and Estonia, the authorities regulate the amortization rates and/or maturities in order to lock down the loan repayment amounts and schedule.[1]

In the Finnish context, new mortgages are regulated by a *loan-to-collateral* (LTC) restriction. However, the working group of the Ministry of Finance has proposed supplementing the toolkit with a new debt-to-income instrument to fill out Finland's macroprudential framework. Their reasoning is that the LTC regulation is insufficient to curb the increase in household debt levels and slow house price inflation during a boom[2], and respectively, in preventing the potential adverse effects caused by the bursting of a debt-induced bubble.

In this study, we observe a negative association between fast-paced expansions in household debt and subsequent economic growth as recorded in Finnish macroeconomic data. Similar findings have been obtained by Mian et al. (2017) for a panel of countries and Mian and Sufi (2010) for the United States. Figure 1 displays the relationship between the average future quarterly growth in GDP for four and eight quarters ahead against contemporaneous values of two different notions of household leverage: average quarterly growth in the household debt-to-GDP ratio and the household debt-to-income trend deviation. The relationship is negative for each combination of forecast horizon and definition of debt variable, but the effect is clearest for the household debt-to-income trend deviation and most pronounced for the eight-quarters-ahead forecasting horizon.

Focusing on the bottom-left subplot of Figure 1, there are clusters of influential observations at the top-left and bottom-right quadrants, which carry a lot of weight in estimation results. This is a good example of why one should be interested in the distribution of the observations as a whole. While these rare observations are influential in analysis of the average relationship between household debt growth and future GDP growth, given that these events are extremely costly when occurred we emphasize the monitoring of the build up of the risks at the tails of the distribution as well, if possible.

Figure 2 is another illustration of this matter. The distribution of the forecast errors is asymmetric and has thick left tail, meaning that extreme events tend to be negative. In our

[1] A comprehensive review of the banking regulation in Europe can be found in Review of Macroprudential Policy in Europe, ESRB (2019).

[2] Model-based evidence of such a phenomenon can be found in Millard, Rubio, and Varadi (2021) and Chen, Finocchiaro, Lindé, and Walentien (2020).

analysis we find robust evidence that the probability of these large negative events is negatively associated with rapid household debt expansion.

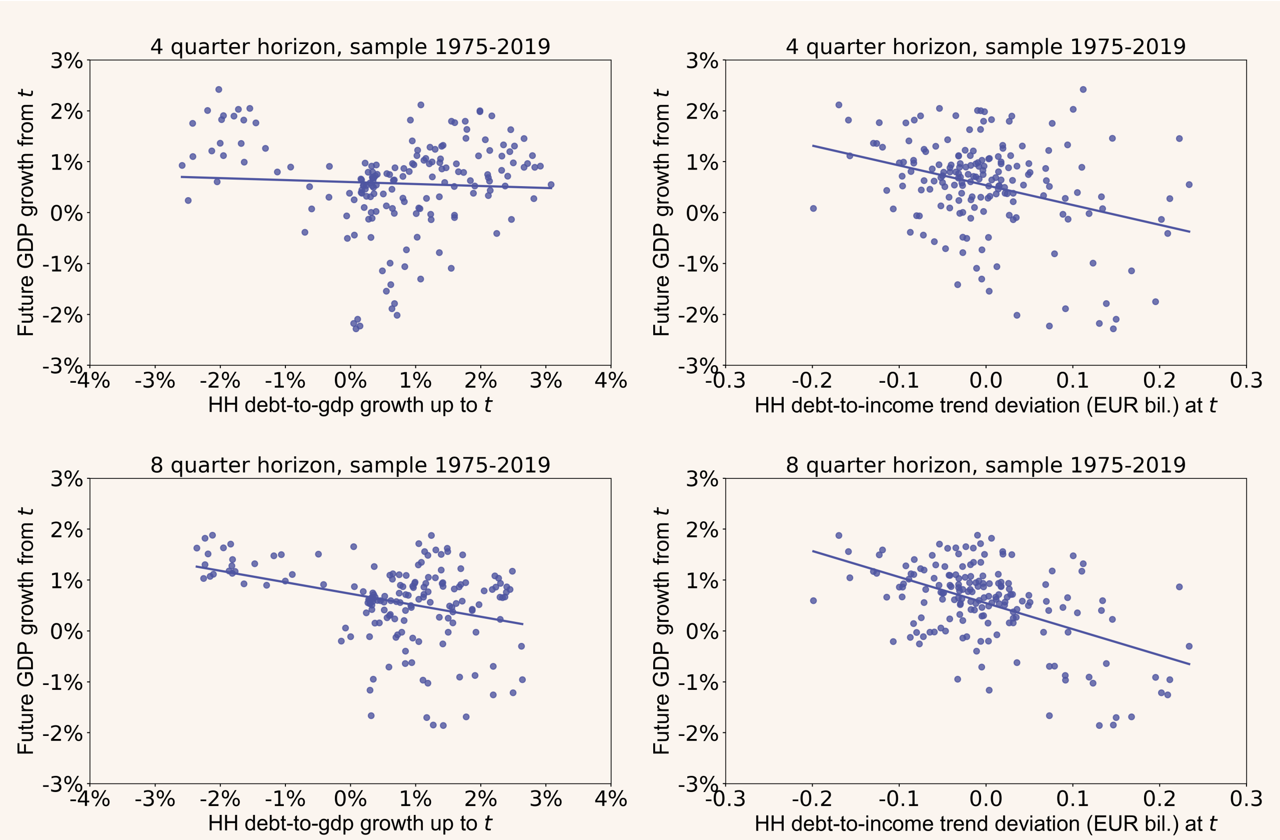

Figure 1: Simple OLS regressions $Y \sim X$. In each plot, Y is the average future GDP growth from time t to $t+h$. For the top row, $h = 4$ quarter horizon; for the bottom row, $h = 8$ quarter horizon. X represents two different credit variables. For the two plots on the left, X is the average quarterly growth rate of the HH debt-to-GDP ratio between $t-h$ and t. For the two plots on the right, X is the HH debt-to-income trend deviation.

The main purpose of this report is to shed light on the relationship between growth vulnerabilities and domestic household debt. While this relationship is ambiguous and a subject of debate, there is substantial evidence to bolster the hypothesis that high debt levels and/or rapid debt accumulation in expansion phase make the economy more prone to severe downturns. Using heterogeneity between US counties, Mian and Sufi (2010) show that the more leveraged households were before the Great Recession, the more their consumption was cut and the more severe the crisis. The IMF's Global Financial Stability Report (IMF, 2017, Chapter 2, Household Debt and Financial Stability) presents similar results for a panel of countries. Turning to micro-level data, a similar pattern is identified in Chapter 6 of Bunn, Rostom, Chadha, Chrystak, Pearlman, Smith, and Wright (2016). Further, Andersen, Duus, and Jensen (2016) find a negative connection between fast household debt expansion and subsequent spending declines in Danish household data.

These empirical results are consistent with a theoretical explanation known as the *credit-driven household demand channel*. A good summary can be found in Mian and Sufi (2018). Authors characterize the cycle in three steps. At first, increased credit supply channels into consumption. At the second stage, increased consumption creates a boom. The third phase is the bust, which becomes more severe as more households are obliged to cut their consumption

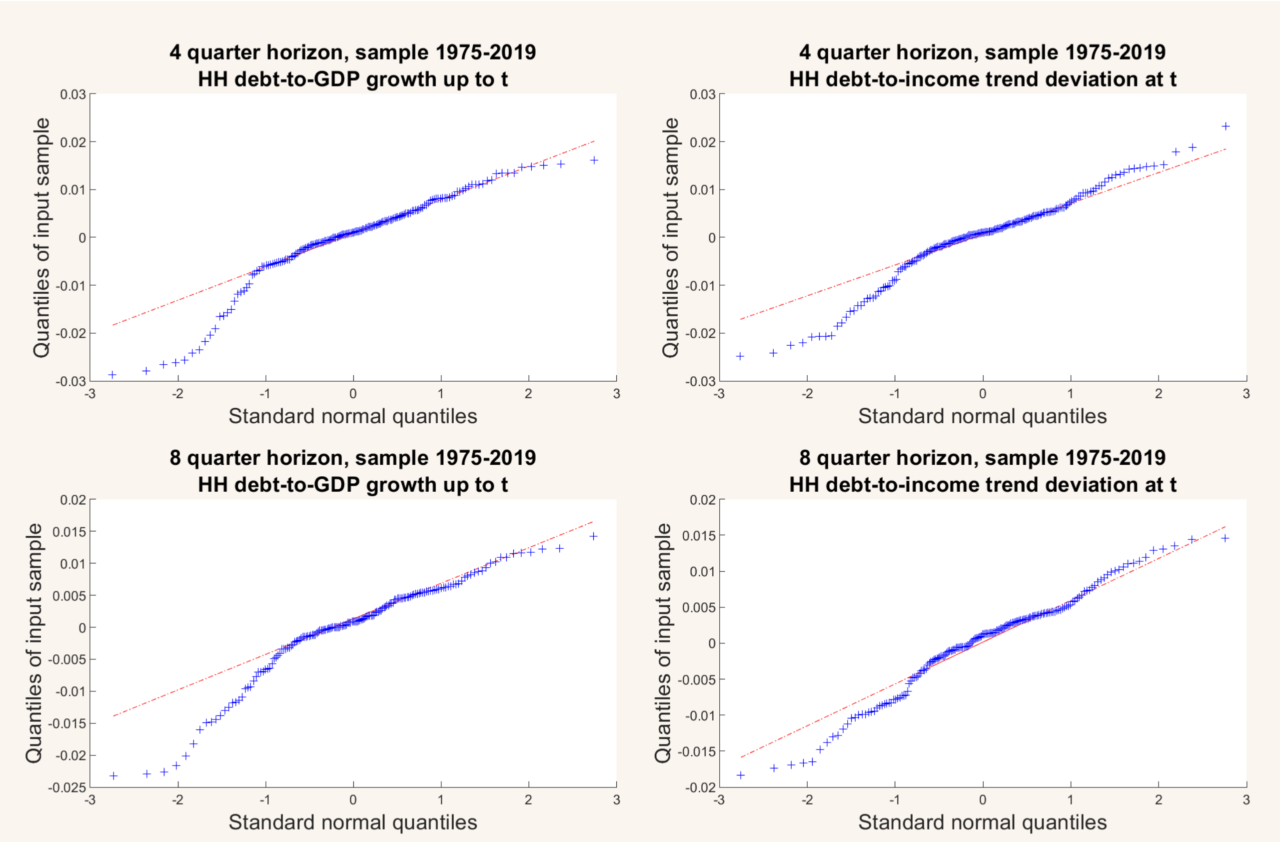

Figure 2: Residuals from regressions in Figure 1. For the top row, $h = 4$ quarter horizon; for the bottom row, $h = 8$ quarter horizon. For the two plots on the left, the explanatory variable is the average quarterly growth rate of the HH debt-to-GDP ratio between $t - h$ and t. For the two plots on the right, the explanatory variable is the HH debt-to-income trend deviation.

as their debt-service ratio rises. One of the more prominent pieces of evidence for this causal effect of an increased debt burden leading to reduced consumption can be found in Verner and Gyöngyösi (2020), which utilizes a natural experiment in Hungary. Our intention is not to validate any such mechanisms behind the relationships we report. The association between rapid household debt expansion and increased crises probabilities is, however, compatible with such debt-driven household demand channel.

Another reason for the severity of a bust may be the occurrence of a banking crisis in the aftermath of the downturn. Seminal results on the predictive power of leverage on a financial crisis are provided in Demirgüç-Kunt and Detragiache (1998), Demirgüç-Kunt and Detragiache (2005), Kaminsky and Reinhart (1999), Lowe and Borio (2002); Borio and Lowe (2002), and Reinhart and Rogoff (2009). Borio and Drehmann (2009) find that including the private debt level in prediction of currency crises improves model performance relative to those that exclude this information. Similar results are documented in Tölö, Laakkonen, and Kalatie (2018), and with specific reference to the Finnish economy in Lainà, Nyholm, and Sarlin (2015).

In the following discussion, we analyze the dependency structure of the future GDP growth probability distribution on household debt. In addition to the negative association found in Figure 1, we show that exuberant expansions in debt accumulation shift the entire GDP distribution and widen the left tail of that distribution. We follow the lead of Adrian, Boyarchenko, and Giannone (2019), and Adams, Adrian, Boyarchenko, and Giannone (2021) with our modeling choices. Using quantile regression methods, the first paper argues that negative tail risks are associated with tightening financial conditions, but upper quantiles are less sensitive to these changes. The latter paper argues that the same relationship can also be found between financial conditions and employment risks. Prasad, Elekdağ, Jeasakul, Lafarguette, Alter, Feng, and Wang (2019) explains the use of a quantile regression framework for predictive purposes in a country surveillance application. Theory of quantile regression methods in econometrics is credited to Koenker and Bassett Jr (1978) and Bassett Jr and Koenker (1978).

The rest of the article is organized as follows. Section 2 describes our modeling framework, i.e. the quantile regression. Section 3 introduces used data and transformations applied on the raw series. The main results and robustness checks are laid out in section 4. Section 5 concludes.

2 Quantile regressions

We study the effects of household indebtedness on different parts of the conditional future GDP growth distribution. A standard *ordinary least square* OLS regression is used to explain the conditional mean of the distribution as a linear combination of explanatory variables, while a *least absolute deviation* (LAD) regression does the same for the median of the distribution. More generally, the purpose for the use of quantile regression is to analyze the entire shape of the distribution of a random variable Y. For any probability $\tau \in (0,1)$, the quantile function $Q_Y(\tau)$ is defined as $P(Y < Q_Y(\tau)) = \tau$, for which, conditional on variables in X, we assume a linear form $Q_Y(\tau|X = x) = x'\beta$.

We model the quantiles of average real GDP growth from t to $t+h$, for $t = 1, \ldots, T-h$, denoted by Y_h. A vector of conditioning variables at time t is denoted by X_t, and it includes the debt variable of interest, a set of controlling variables, lagged values of the variables, and a constant. The coefficient vector $\beta_h^{(\tau)}$ of the quantile regression is estimated by minimizing the weighted absolute value of errors,

$$\hat{\beta}_h^{(\tau)} = \underset{\beta_h^{(\tau)} \in \mathbf{R}^K}{\operatorname{argmin}} \sum_{t=1}^{T-h} \left(\tau \ \mathbf{I}_{(Y_h > X_t' \beta_h^{(\tau)})} + (1-\tau) \ \mathbf{I}_{(Y_h \leq X_t' \beta_h^{(\tau)})} \right) |y_h - x_t' \beta_h^{(\tau)}|, \tag{1}$$

where $\mathbf{I}_{(\cdot)}$ denotes the indicator function and K is the number of the coefficients in $\beta_h^{(\tau)}$. A consistent estimator for any τ^{th} quantile of Y_h, conditional on X_t, is given by $\hat{Q}_{Y_h|X_t}(\tau|X_t = x_t) = x_t'\hat{\beta}_h^{(\tau)}$. Asymptotic distribution for the estimator can be found, for example, in Greene (2008), Chapter 7.

3 Data

We use data from various reports[3]. GDP statistics are taken from the quarterly national accounts reported by Statistics Finland. Quarterly values for household income, obtained from the quarterly sectoral accounting of Statistics Finland, are only available from 1999 onwards.

[3]All series, except for the credit series from BIS, are queried via the Bank of Finland's internal database. The BIS series are queried using the public API of the BIS Statistics Warehouse.

Observation before 1999 are linearly interpolated from annual observations provided by Statistics Finland's national accounting. The consumer price and house price indices of Statistics Finland are provided at monthly and quarterly frequency, respectively. Household and non-financial corporate credit data are provided by the BIS Statistics Warehouse. The 12-month Euribor rate is used as the reference rate for the euro era, starting in 1999. Moving back into the pre-euro era, we use Finnish 12-month Helibor interbank rate for the period beginning in 1987. For the period 1975 to 1986, we use an estimated series from Finnish markka forward contracts. The cost of household debt is measured using the interest rate of new mortgages as given in the Bank of Finland's Monetary and Finance Statistics[4].

We focus here on the relationship between household debt and the shape of the probability distribution of future GDP growth. The left subplot in Figure 3 displays the evolution of real GDP over our complete sample (from 1975Q1 to 2019Q4), as well as real household debt and household disposable income. Household debt exhibits a more than seven-fold increase during our sample period. Relative to income, the debt of households more than triples. The only substantial decline in the real debt level occurs in the aftermath of the Finnish Great Depression of the early 1990s. The debt level hits its fastest pace right before the onset of the depression. Towards the end of our sample, the growth in the debt stock remains fairly stable, especially from 2015 onwards.

We stationarize debt level variables by de-trending them using a two-sided Hodrick-Prescott filter with a smoothing parameter of 1600. The top-right subplot in Figure 3 shows the trend deviation for real household debt, as well as the trend deviation for real household income. We observe that the household debt trend deviation peaks soon after periods where household debt growth hits its fastest pace. Trend deviation describes periods when the original series exhibit exuberant (upward or downward) behavior relative to values in the (near) past and (near) future. This makes trend deviation in household debt a natural choice for describing possibly vulnerable states in terms of household indebtedness. In essence, we want to assess whether exuberant accumulations in household debt can be linked with growth vulnerabilities.

The bottom-right subplot of Figure 3 charts the evolution of the average future quarterly real GDP growth at the $h = 8$-quarter horizon. We use this series for different values of h as the left-hand side variable in the regressions. For comparison, we also chart the quarterly GDP growth rate.

[4]The series is public from 2010 onward: `https://www.suomenpankki.fi/en/Statistics/mfi-balance-sheet/older-news/2016/kotitalous_ja_yrityslainojen_laskennalliset_korkomarginaalit_suomessa_chrt_en/`

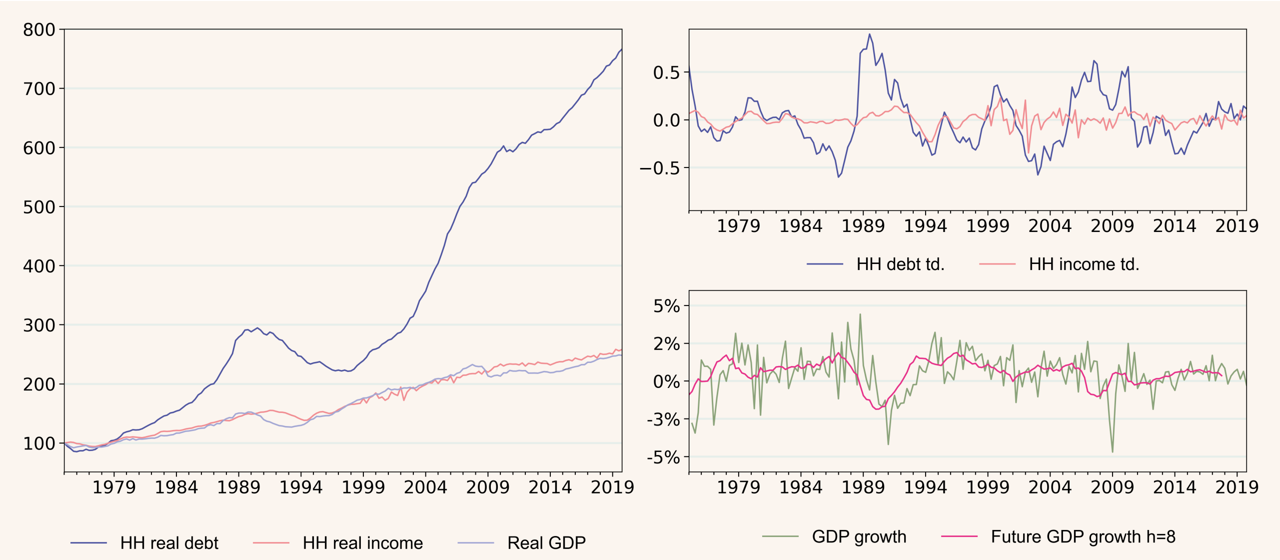

Figure 3: The plot on the left displays real household debt, real household disposable income, and real GDP. Series index: 100 = 1975. Top right plot displays of real HH debt trend deviation and income series in EUR billion. Bottom right plot displays current Q-o-Q real GDP growth, as well as average future real GDP growth. h = 8 quarters ahead from time t.

4 Results

This section outlines the main results from our investigation into the relationship between exuberant periods of household debt and future GDP growth. In subsection 4.1, we provide estimation results of the baseline specification of our quantile regression model. Subsection 4.2 highlights an important question from the viewpoint of macroprudential analysis: Why concentrate on household debt? Subsection 4.3 provides robustness checks for our model in terms of the different model specifications.

The dependent variable in each specification is the average quarterly real GDP growth rate from t to $t + h$. In addition to the debt variable of interest and control variables, each specification includes a constant. We report the estimation results for quantiles $\tau \in [0.1,\ 0.9]$ with 5%-point increments, for four forecast horizons, i.e. $h = 4$, 8, 12, and 16. The Appendix contains tables of estimation results for each of the specifications in this section. The tables include estimates of all the coefficients for all of horizons, for quantiles $\tau = 0.2$, 0.5, and 0.8, along with their asymptotic p-values.

4.1 Main results

In the baseline specification, we use *household real debt trend deviation* as our variable of interest. What matters for us is either the size of debt relative to the rest of the economy (Mian et al. 2017) or the debt-servicing costs relative to income (Drehmann and Juselius, 2012). Debt growth per se might provide a rather dull discussion if increases in household income or GDP coincide with it. To avoid this, we control for GDP growth and the household income trend deviation in order to compare periods with similar paces of income accumulation[5]. In the robustness section, we run a similar regression with *trend deviation of household debt to income* as the debt variable of interest to make sure that our results hold when the debt variable is explicitly normalized by household income.

Our choices of the remaining control variables, growth in house prices and the cost of household debt (measured by interest rate of new mortgages) is motivated by an assumption that they are drivers of debt accumulation and that adjusting for them makes conclusions about the relationship of debt to GDP growth more accurate. Conversely, growth in the consumer price index and interest rate are important determinants of the business cycle, so they are adjusted to better explain variation in the dependent variable. First lags of all control variables and the debt variable are included on the right-hand side to adjust for autocorrelation in the series. To avoid potential problems with the quality of the data in the early part of the sample, the data in the baseline specification start at 1980Q1 and end at 2019Q4.

A causal interpretation of effects of exuberant debt accumulation on future GDP growth would require a more carefully laid out research design. However, the purpose of our analysis here is simply to compare how different paces of debt accumulation are related to subsequent GDP growth.

Figure 4 displays estimated coefficients for contemporaneous (time t) debt variable. Each subplot represents quantile regression estimates for a different horizon h. We also display bootstrapped confidence intervals for the null hypothesis that the regression coefficient is constant across all quantiles.[6] For comparison, the solid red line depicts the value of the OLS estimate, and the dashed lines the 95% asymptotic confidence intervals for this coefficient.[7]

[5]In the robustness section, we test the baseline specification when adjusting for growth rate in household income instead of income trend deviation. The results do not change qualitatively.

[6]We follow Adrian et al. (2019) in defining uncertainty estimates and derive bootstrapped confidence intervals via simulated data from vector autoregression. Specifically, we simulate 1000 data samples from the VAR(2) model $Y_t = A_0 + A_1 Y_{t-1} + A_2 Y_{t-2} + \varepsilon_t$, where Y_t contains all the same (contemporaneous) variables as on the right-hand side of the corresponding quantile regression. Next, we fit the quantile regression on each simulated data sample and order obtained coefficients for each explanatory variable. Coefficients falling on, say, 5th and 95th percentile, represent boundaries for 90 % bootstrapped confidence interval under the null hypothesis of no tail effects. Under the null hypothesis, the true data generating process is a linear model for which there might be contemporaneous and dynamic correlation between all the variables, but the shape of the distribution of one variable should not change the conditional on other variables, except for its location.

[7]Quantile regerssion estimates are produce with class *QuantReg* of Python library *statsmodels* (Seabold and Perktold 2010, version 0.11.1). VAR simulations are performed with class *varm* of MATLAB (2019).

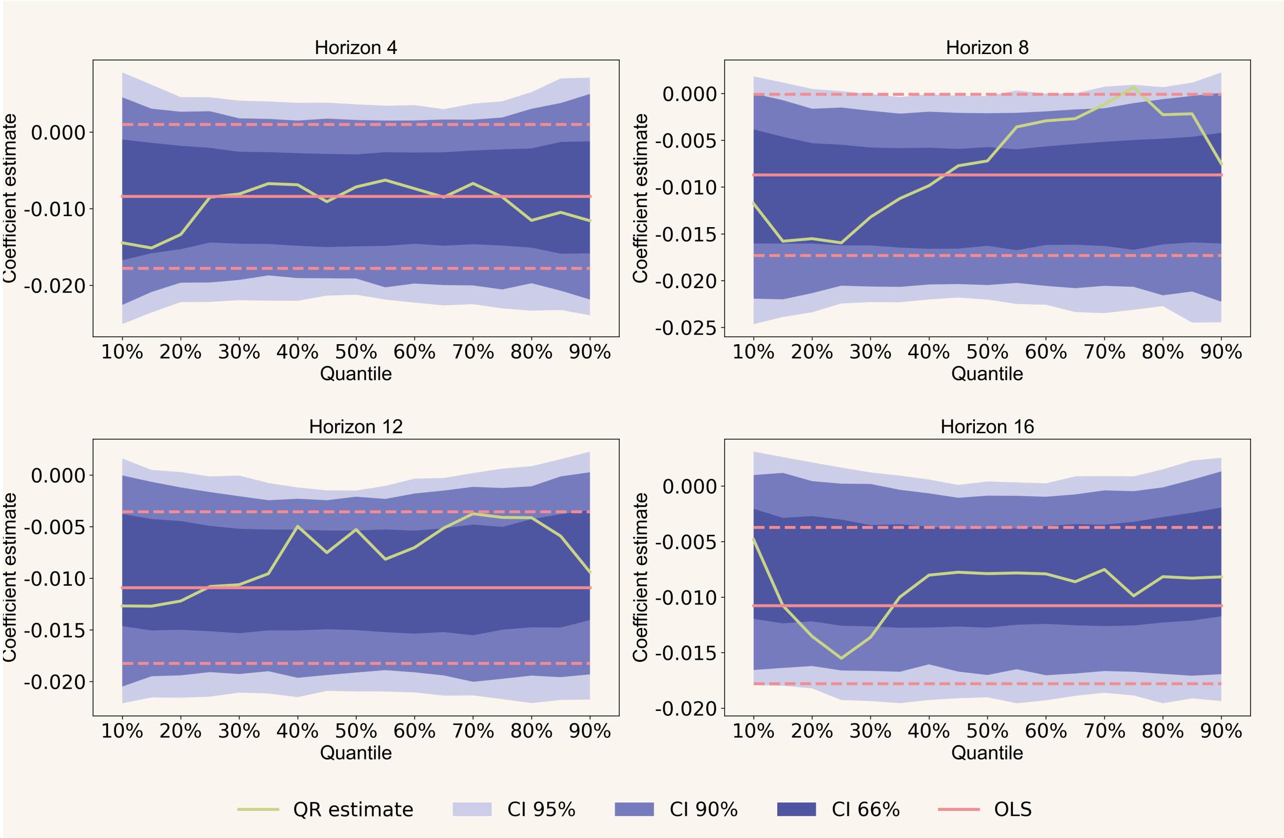

Figure 4: Quantile regression coefficients for household real debt trend deviation. In each plot, the LHS variable in the regressions is the average future GDP growth from time t to $t+h$, where h is the given horizon. Control variables include Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, their first lags, and the first lag of the debt variable. Shaded regions denote VAR-bootstrapped confidence intervals for varying levels. A similar OLS estimate is shown with dotted lines representing 95% confidence intervals (HAC standard errors with 1 lag and small sample correction). Sample runs from 1980 to 2019. Quantiles are shown for interval [10%, 90%] with 5 percentage point increments.

We draw the following conclusions from Figure 4. First, for each horizon, the 50% quantile (median) coefficient, as well as the OLS coefficient, is negative. This implies that the association between debt variable and future GDP growth is negative on average (as in naive OLS regressions in Figure 1). In the case $h = 8$, for example, the OLS estimate is about -0.0087. This means that, on average, an EUR one billion increase in household real debt trend deviation (see Figure 3) is associated with 0.87 %-point decrease in average quarterly future GDP growth.

Second, the coefficient estimates are negative for each quantile, implying that increases in debt variable are negatively associated with each part of the future GDP distribution. Intuitively, this means that when comparing a period of exuberant debt accumulation to a period with more typical debt behavior (with control variables at the same levels over both periods), the overall probability distribution of future GDP growth (not just left tail) in the former period shifts to the left compared to the latter period.

Third, for horizons $h = 4$, 8, and 12, estimates for lower quantiles are clearly more negative than those for the median, implying that increases in debt variable are associated with a widening of the left tail of the GDP distribution (in addition to the general shift in the distribution). The profile of the estimated coefficient line for horizon $h = 16$ is (more or less) flat, implying no particular tail effects.

Fourth, for horizons $h = 8$ and 12, estimates for right-tail quantiles are around the same level as the median or approaching zero. This means that increases in debt variable are associated with shifts of similar size or smaller in the right tail of future GDP distribution compared to the center of the distribution. The third and fourth observation together point in the direction advocated by Adrian, Grinberg, Liang, and Malik (2018) and Adrian et al. (2019), who find that looser financial conditions lead to worse growth-at-risk in the medium term, and that this phenomenon is amplified by a credit boom.

Fifth, the result of a widening future GDP distribution (as a function of the chosen debt variable) show signs of statistical significance. For the horizons $h = 8$ and 12, the multiple subsequent quantiles in the right tail breach the bootstrapped intervals of 90% and 66% confidence, respectively. This indicates that the null hypothesis of a constant regression coefficient across all the quantiles can be rejected. In the case $h = 8$ one right-tail coefficient estimate breaches 95% confidence bound. Another concept of statistical significance is introduced in Table 1 in the Appendix. The p-values (calculated from asymptotic quantile regression standard errors) indicate that the coefficients for contemporaneous debt variable are negative and different from zero by 90% or more confidence across most horizons and quantiles. Further, when quantile estimates in Figure 4 are compared against the HAC robust 95% confidence bands for similar OLS estimate, the results show that where we breach the 90% bootstrapped bounds (66% bootstrapped bounds) for horizon $h = 8$ ($h = 12$) are cases where quantile estimates approach the confidence interval for OLS estimate.[8]

All in all, the baseline results display clear signs that the periods when vulnerabilities build coincide with periods of exuberant household debt behavior. This is consistent with the theoretical explanation of demand-driven household debt channel of Mian and Sufi (2018) referenced in section 1: the greater the expense of carrying debt, the more households need to cut spending in busts to be able to keep servicing their loans. We make no causal claims based on our results, so they cannot be taken as validation of such an effect. Nevertheless, the data are clearly consistent with the theory.

4.2 Why focus on household debt?

The results in Figures 5 and 6 justify our main focus of household debt. While the regression behind the figures is similar to our baseline as in Figure 4, we also include trend deviation of non-financial corporate debt in the right-hand side variables (including first lag). The rest of the control variables are the same as in the baseline regression specification.

Our estimation results reveal that the tail association of household debt remains (Figure 5). However, the coefficients for the firm debt trend deviation show no negative average association nor any particular tail effects (Figure 6). Thus, it is household debt, not firm debt,

[8]We are not aware of a formal statistical test for testing the exact null hypothesis that the coefficients differ across quantiles, i.e. that the slope of the coefficients plotted against the quantiles is different from zero. We consider it encouraging that in both plots $h = 8$, 12, there are several subsequent quantiles that breach the mentioned confidence bound intervals. One can also compare the regression coefficients of the tails against the confidence bounds, say, of the coefficient of the median, or test if the difference between the two is statistically significant. More thorough conclusions would require multiple testing regimes.

that is associated with the negative outcomes in future GDP growth. In subsequenct regression specifications, we omit the non-financial corporate debt.

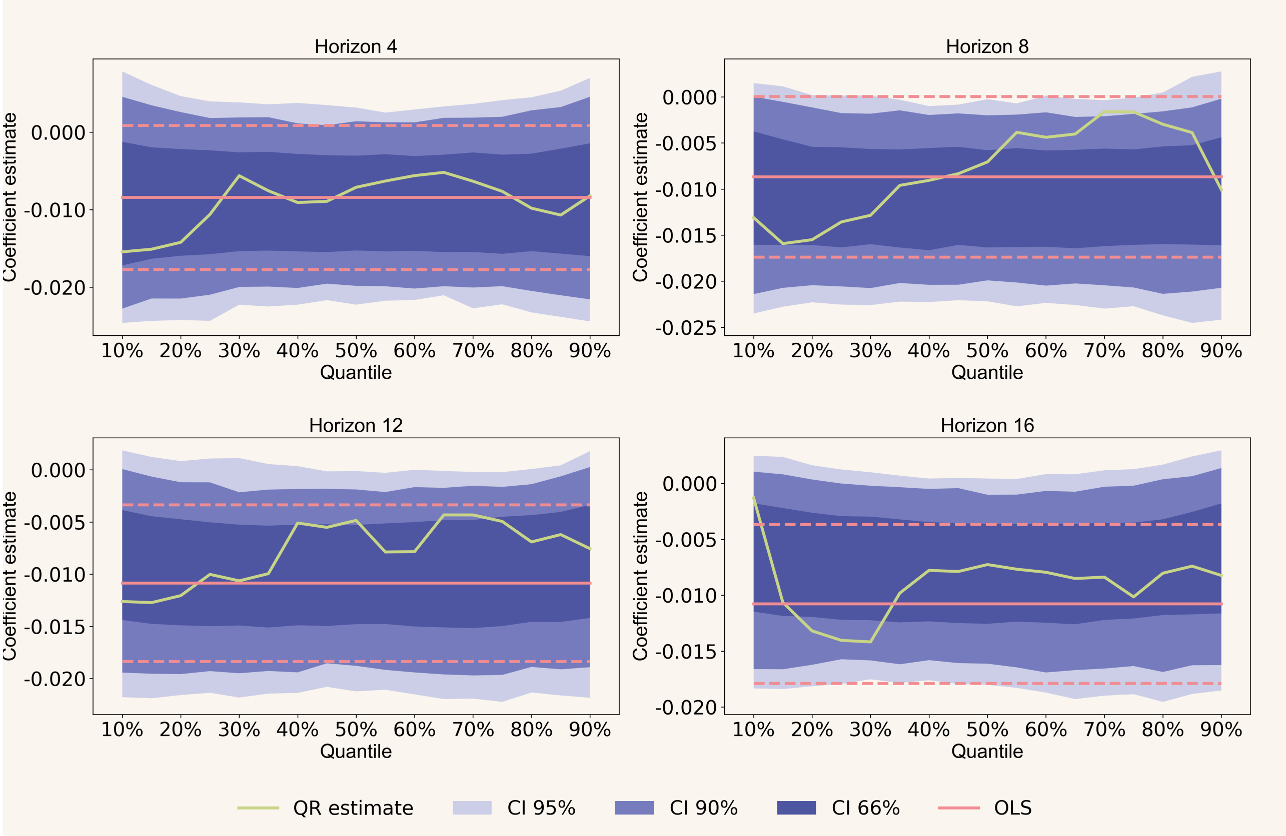

Figure 5: Quantile regression coefficients for real household debt trend deviation. In each plot, the LHS variable in regressions is average future GDP growth from time t to $t+h$, where h is the given horizon. Control variables include Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, real non-financial corporate debt trend deviation, their first lags, and the first lag of the debt variable. Shaded regions denote VAR-bootstrapped confidence intervals for varying levels. Similar OLS estimate is shown with dotted lines representing 95% confidence intervals (HAC standard errors with 1 lag and small sample correction). Sample runs from 1980 to 2019. Quantiles are shown for interval [10%, 90%] with 5 percentage point increments.

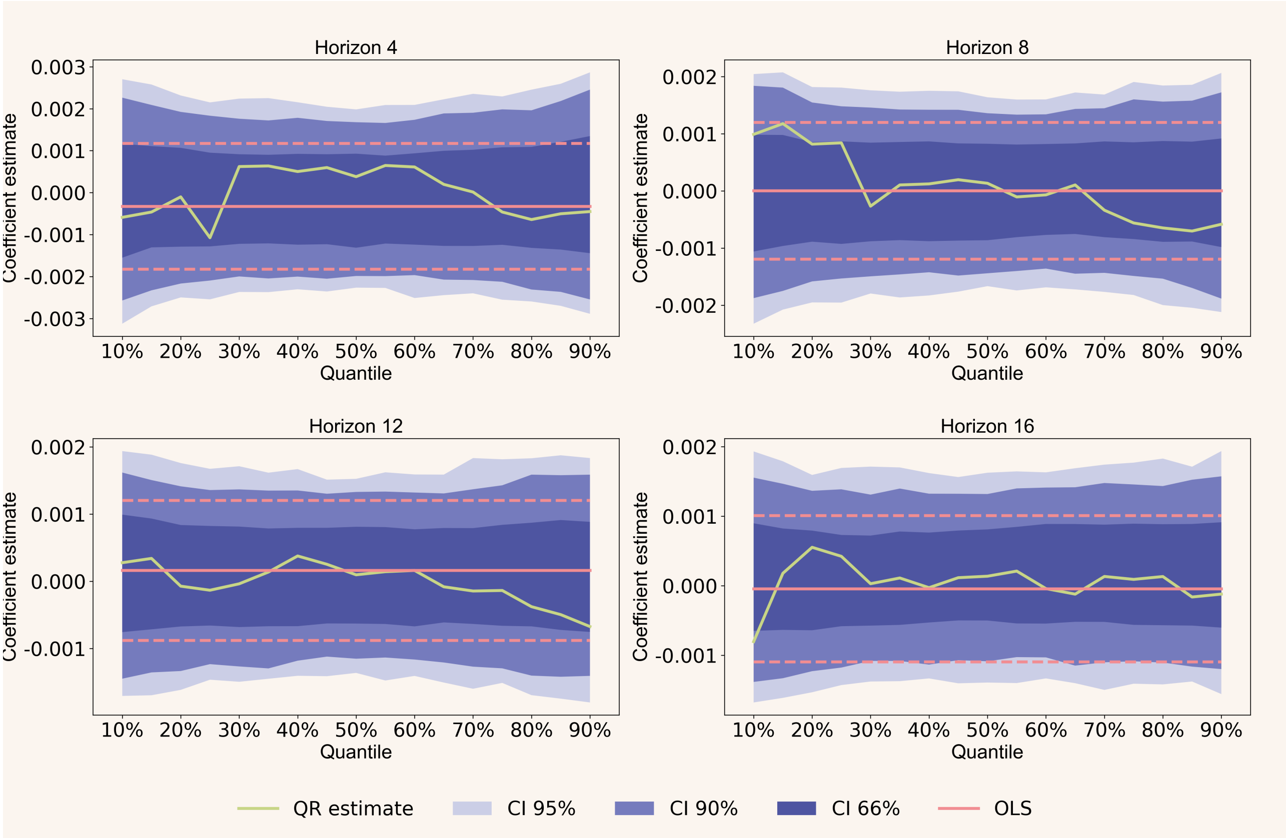

Figure 6: Quantile regression coefficients for real non-financial corporate debt trend deviation. In each plot, the LHS variable in regressions is the average future GDP growth from time t to $t + h$, where h is the given horizon. Control variables include Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, real household debt trend deviation, their first lags, and the first lag of the debt variable. Shaded regions denote VAR-bootstrapped confidence intervals for varying levels. Similar OLS estimate is shown with dotted lines representing 95% confidence intervals (HAC standard errors with 1 lag and small sample correction). Sample runs from 1980 to 2019. Quantiles are shown for interval [10%, 90%] with 5 percentage point increments.

4.3 Robustness

We run several regressions to ensure the robustness of our findings. The results from the robustness checks are described in this subsection, while related figures and tables can be found in the Appendix.

First, we test if the results hold when we make changes to variables in the right-hand side of baseline regression specification. Here, we test changing the debt variable of interest from the real household debt trend deviation to the debt-to-income trend deviation. The results are depicted in Figure 7.

We next test using household income growth as a the control variable in place of the trend deviation of household income. These results are presented in Figure 8. Control variables in both figures are the same as in the baseline regression in Figure 4.

Compared to our baseline result, we see that the upward trending profile of coefficient estimates for the 8- and 12-quarter horizons remain intact in both figures. In Figure 7 we see a stronger negative association in the left-tail estimates for $h = 4$. In terms of statistical significance, case $h = 12$ remains more or less the same. In case $h = 8$, the right-tail estimates suffer in terms of statistical significance, but, on the other hand, the left-tail estimates have similarly improved. The case of the 16-quarter horizon is more or less the same as for the baseline.[9] Turning to Figure 8, the results are well aligned with the baseline, although in case of horizon $h = 4$ the right-tail estimates collapse compared to the baseline. Nevertheless, the profiles of coefficient lines in cases h =8, 12 are clearly upward trending, and the statistical significance of the results is comparable to our baseline results. We conclude that the changes in the definition of the debt variable or income control do not qualitatively change the main results.

Our second robustness check is whether individual crisis periods are the main drivers of the baseline results. We also test for alternative sample starting points. For this purpose, we sample the data in four different periods. First, we use the full sample from 1975 to the end of 2019 (the baseline specification excludes the first five years). The second sample, 1994 to 2019, resembles the period after the Finnish Great Depression of the early 1990s.[10] Third, the sample from 1975 to 2007 illustrates our results when the financial crisis of 2008 and European debt crisis are excluded. Finally, the sample from 1975 to 1989 illustrates the results prior the Great Finnish Depression. We provide the estimation results using eight quarter forecasting horizon, $h = 8$, and the debt variable is the households debt trend deviation. Control variables are the same as in the baseline results.

The results are displayed in Figure 9,[11] for the eight-quarter forecasting horizon, $h = 8$. We see that with the longest sample results match well with the baseline specification. The upward sloping profile of quantile coefficient line is present in the sample excluding the Great Finnish Depression of the 1990s, but the median and OLS estimates are now about zero. In contrast, in the sample excluding the financial crisis of 2008 median estimate is again negative and the profile of the coefficients is rather flat. Finally, the sample excluding both crisis periods display negative association and a rather flat profile. It is worth noticing that the sample size is likely too small for reliable identification of the tail effects.

The observations point to the fact that our results of negative average association and asymmetric tails association become more uncertain when crisis periods are removed from the sample. In our view, this result is not a big surprise due to the short sample sizes, but also given the observation made in section 1 that removing realized tail events from the sample may obscure identification of negative, non-linear effects. While acknowledging that the analysis of tail events is rather uncertain using short sample sizes, results in Figure 9 reinforce our conclusion about the negative association between household debt and the left tail of the GDP distribution. It also reinforces our conclusion about the negative average association between faster household debt accumulation and future GDP growth, but this relationship is most likely

[9]The OLS estimate for the debt variable of interest in case $h = 8$ is about -0.038. This means that a one percentage point increase in trend deviation of household debt-to-income is associated with a decrease in average future GDP growth of 0.038 percentage points.

[10]The Great Finnish Depression of th early 1990s was accompanied by a devaluation of the Finnish markka. Since the opening of the Finnish capital markets in the late 1990s, a portion of Finnish debt has been denominated in other currencies. The devaluation increased the value of markka-denominated debt levels, and thus the dynamics of the debt and economic growth might have changed between the Finnish depression and the financial crises in 2007.

[11]Due to short samples in Figure 9 we avoid running VAR-simulations and do not display bootstrapped confidence intervals. Instead, asymptotic OLS and quantile regressions confidence intervals are shown.

driven by outlier crisis events and is prone to estimation sample period.

The last set of robustness checks is to investigate the effects of the major structural changes in Finnish economy. Interest rate rationing ended in 1988 and by 1989 Finnish capital markets had gone through major shifts toward the more open and competitive form (Vihriälä, 1997; Hyytinen, Kuosa, and Takalo, 2003). The next major change happened in 1999 when Finland joined the currency union and adopted Euro. First, by adding a constant dummy variables into regressions, we make sure that that it is not a structural break and a shift in the location of the distribution that would drive our results. For example, if the opening of the capital markets in Finland boosted the growth, it would skew the distribution of the models prediction errors if this shift was not controlled. Figure 10 in the Appendix plots the estimation results with the same set of variables as in our baseline results but adding a constant dummy variable starting at 1989. In Figure 11 we add a dummy that starts in 1999.[12] These additions do not alter the results qualitatively. Note, however, that the capital market dummy is statistically significant for forecasting horizons $h = 4$ and 8, across all quantiles (Table 6), and the Euro-era dummy is very significant basically for all the horizons (Table 7).

Figure 12 displays results for a regression where, in addition to our baseline setting, we have added an interaction term between the capital market dummy variable and new mortgage interest rate. We do this in order to see whether the capital market regulation before the late 1980's would alter the results by restricting the mortgage interest rates to adapt. This additional control variable do not change our main result. Inclusion of the interaction term might still be an improvement, as the term is statistically highly significant for 50% and 80% quantiles (Table 8).

Lastly, there are obvious doubts that the interest rate dynamics changed substantially when Finland joined the monetary union and adapted common currency in 1999. Since the Euro area monetary policy took place, economic activity in small member countries, such as Finland, have had less impact on the interest rates. For this reason, we run the baseline regression but add an interaction term between the interest rate and the Euro era dummy. The results are displayed in Figure 13 and Table 9. Controlling for the Euro area monetary policy does not change the results qualitatively.

5 Conclusions

Our analysis provides support for the hypothesis that household leverage is connected to vulnerabilities in economic growth. We re-establish the result in Mian et al. (2017) that accumulation of household debt is negatively correlated with future economic growth on a medium horizon (from eight to twelve quarters). Our main findings, however, connect this negative relationship to growth vulnerabilities. We find that rapid expansion in household debt is associated with a rise and thickening of the left tail of the GDP distribution. This finding is related to findings in Adrian et al. (2018) and Adrian et al. (2019), but our work focuses explicitly on the role of household debt. Our findings are consistent with the theoretical explanation of the demand-

[12] Asymptotic OLS and quantile regressions confidence intervals are shown instead of VAR-bootstrapped intervals as such bounds are not straightforward to calculate when including dummy variables in the set of explanatory variables.

driven household debt channel of Mian and Sufi (2018), although our results cannot be taken as validation of the theory.

A causal interpretation of effects of exuberant debt accumulation on future GDP growth would require a more carefully laid out research design. Our results establish the historical association between exuberant debt accumulation and future GDP growth in the long Finnish sample. This result is, however, prone to different estimation periods and may vary depending on if the major crises periods are included in the sample, especially the 1990's depression. In order to give advice on macroprudential policy, one should carefully take the equilibrium effects of the policy actions into account. If actions were to be taken to restrict the household debt, this should be a consequence of deep analysis of the costs and benefits of the actions and inactions. This study considers the cost side of the analysis, by introducing risks that might build up during exuberant phases of credit expansion.

Our results are a reminder of possible negative consequences of exuberant household debt growth. Second, our results advocate the use of methods which allow for inspection of nonlinear effects in macroprudential analysis. Simple measures of means or medians might not reveal the build-up of vulnerabilities that are visible mainly at the tails of the future probability distribution.

There are several avenues for future research. The local projection method provides natural opportunities to model effects of exogenous shocks (Plagborg-Møller and Wolf, 2021). Thus far, the impulse responses have usually been derived for the mean effects of exogenous impulses[13]. In the light of our study, one loses valuable information about the potential vulnerabilities by neglecting the effects at the tails. Using information provided by exogenous shocks to the household debt levels, it could be possible to recover information on how a policy action that affects the household leverage is connected to the risk of the tail events. Another path, also pursued in Adrian et al. (2019), would be to confirm the results using a more structural and parametric model. These models have the advantage that the assumption of the parametric form of the model increases the estimation efficiency and provides means for statistical tests about hypotheses. The obvious drawback, however, is that parametric models seldom are as flexible as our semi-parametric framework.

[13] Research towards this direction has been taken e.g. in Chavleishvili and Manganelli (2019).

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Appendix

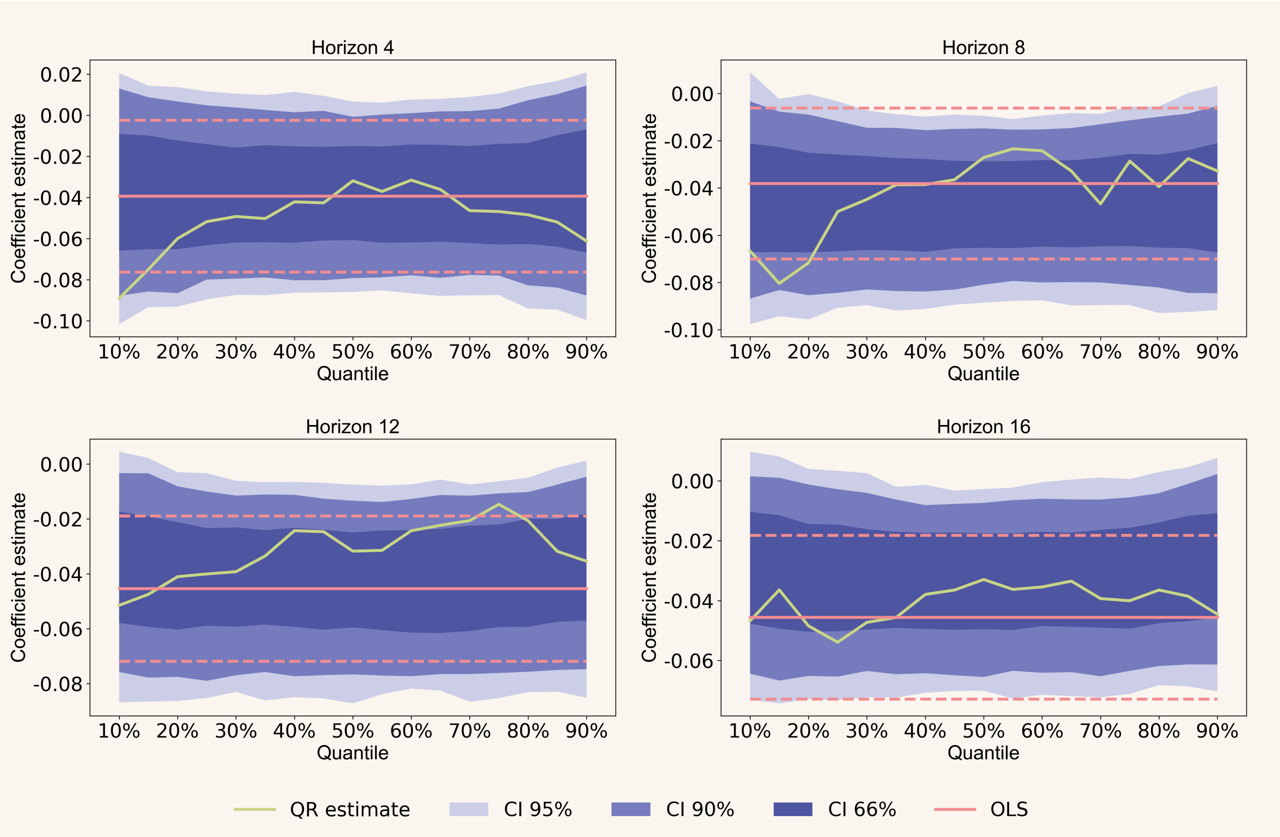

Figure 7: Quantile regression coefficients for household debt-to-income trend deviation. In each plot, the LHS variable in regressions is average future GDP growth from time t to $t+h$,where h is the given horizon. Control variables include Q-o-Q real GDP growth, Q-o-Q houseprice growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, their first lags, and first lag of the debt variable. Shaded regions denote VAR-bootstrapped confidence intervals for varying levels. A similar OLS estimate is shown with dotted lines representing 95% confidence intervals (HAC standard errors with 1 lag and small sample correction). Sample runs from 1980 to 2019. Quantiles are shown for interval [10%, 90%] with 5 percentage point increments.

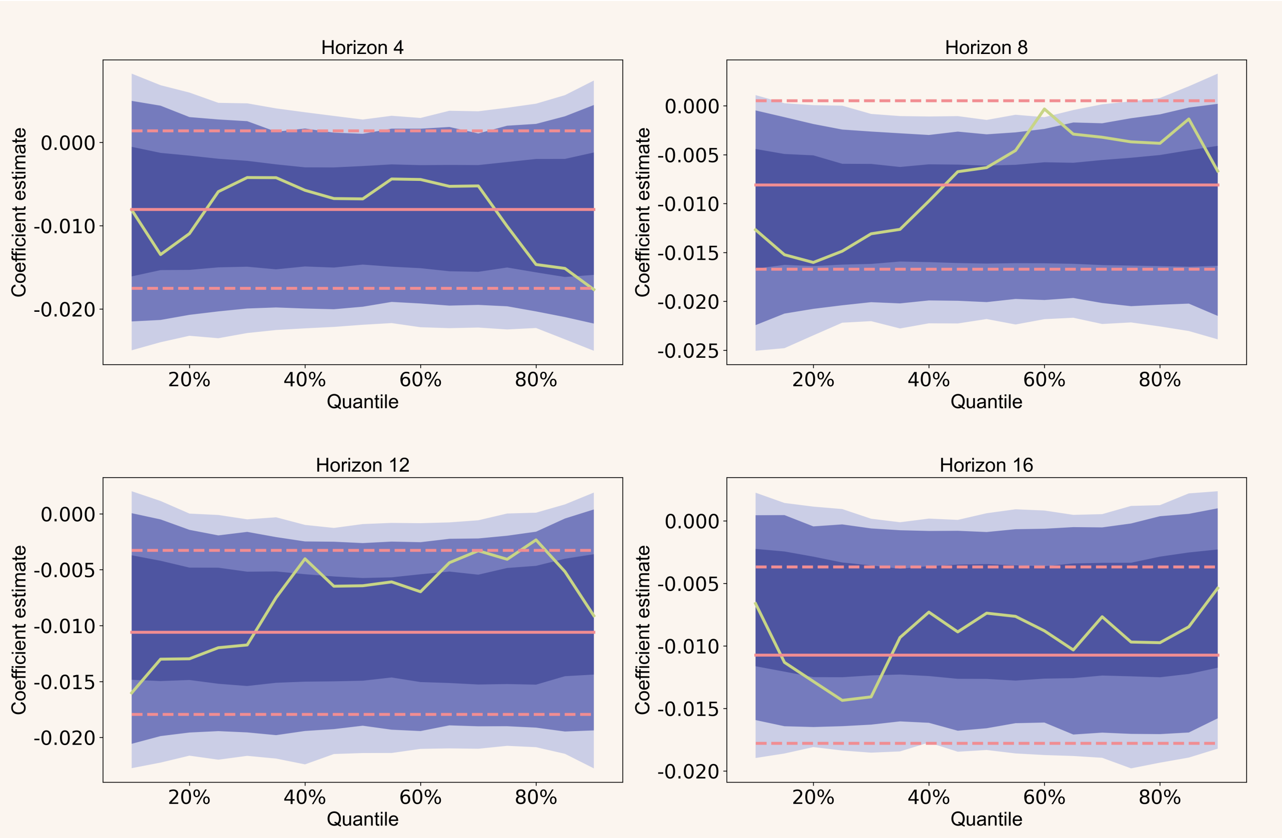

Figure 8: Quantile regression coefficients for household real debt trend deviation. In each plot, the LHS variable in regressions is average future GDP growth from time t to $t+h$,where h is the given horizon. Control variables include Q-o-Q real GDP growth, Q-o-Q houseprice growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, Q-o-Q growth in household real income, their first lags, and first lag of the debt variable. Shaded regions denote VAR-bootstrapped confidence intervals for varying levels. A similar OLS estimate is shown with dotted lines representing 95% confidence intervals (HAC standard errors with 1 lag and small sample correction). Sample runs from 1980 to 2019. Quantiles are shown for interval [10%, 90%] with 5 percentage point increments.

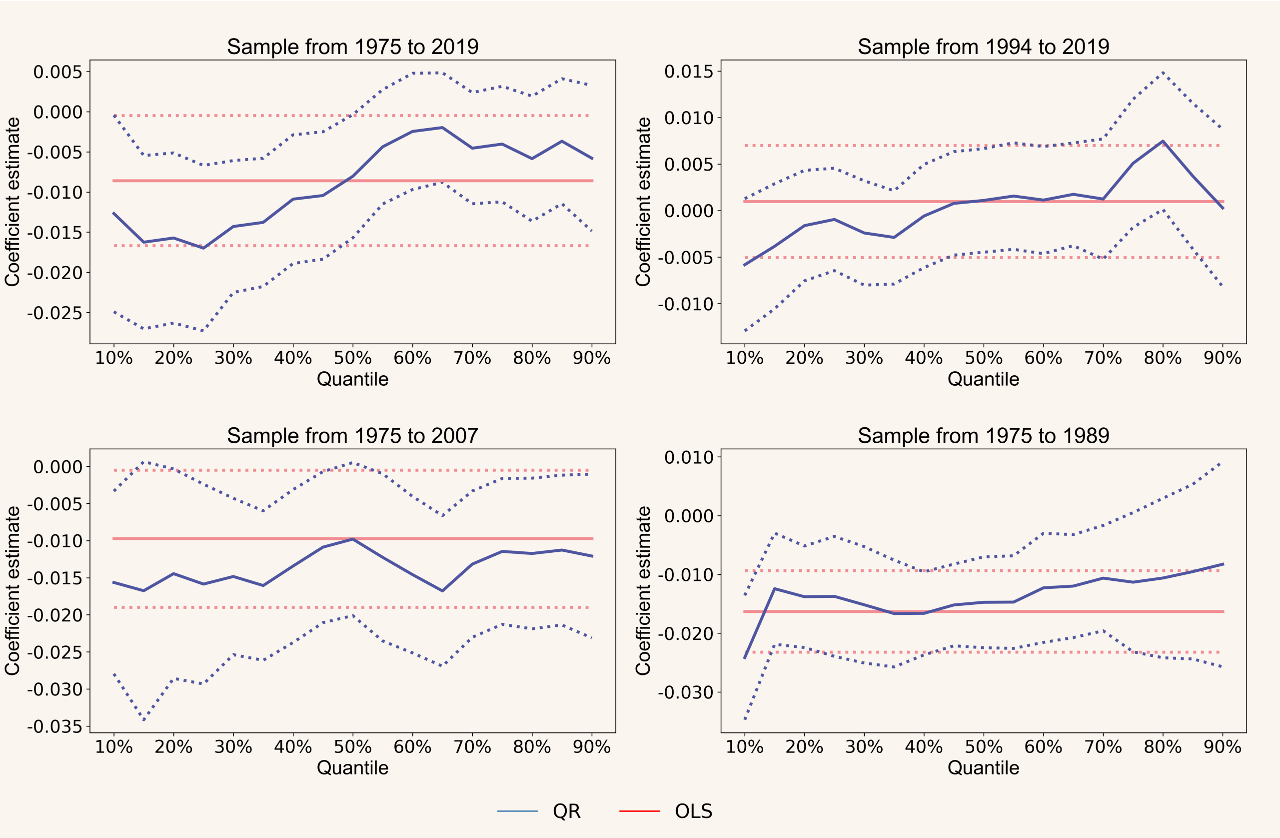

Figure 9: Quantile and OLS regression coefficients for household real debt trend deviation. In each plot, the LHS variable in regressions is average future GDP growth from time t to $t+h$, where h is set to 8 quarters. Control variables include Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, their first lags, and first lag of the debt variable. Dotted lines denote 95% confidence intervals: for QR standard errors are as in Greene (2008), for OLS HAC standard errors with 1 lag and small-sample correction. Quantiles are shown for interval [10%, 90%] with 5 percentage point increments.

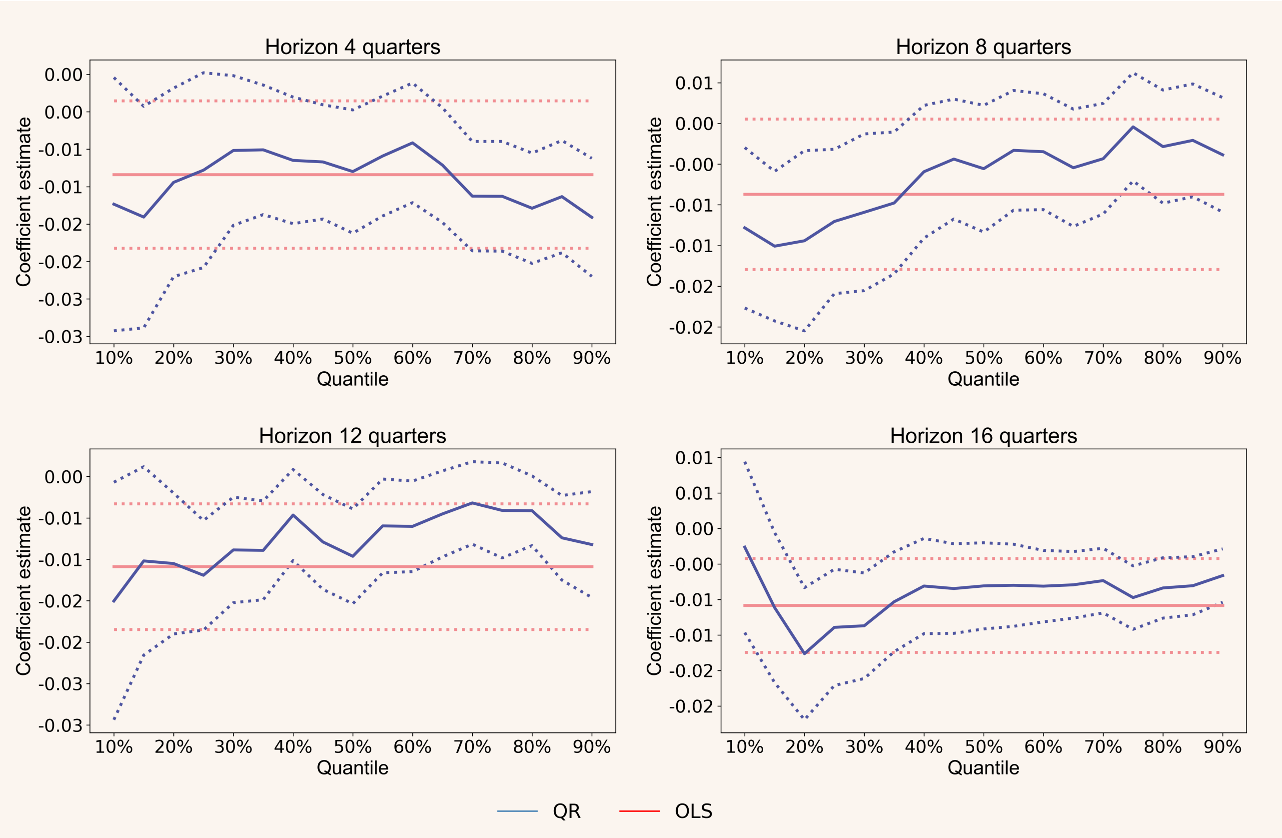

Figure 10: Quantile and OLS regression coefficients for household real debt trend deviation. In each plot, the LHS variable in regressions is average future GDP growth from time t to $t+h$, where h is the given horizon. Control variables include Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, their first lags, and first lag of the debt variable. We also include a dummy variable for time range 1989Q1-2019Q4. Dotted lines denote 95% confidence intervals: for QR standard errors are as in Greene (2008), for OLS HAC standard errors with 1 lag and small-sample correction. Time sample runs from 1980 to 2019. Quantiles are shown for interval [10%, 90%] with 5 percentage point increments.

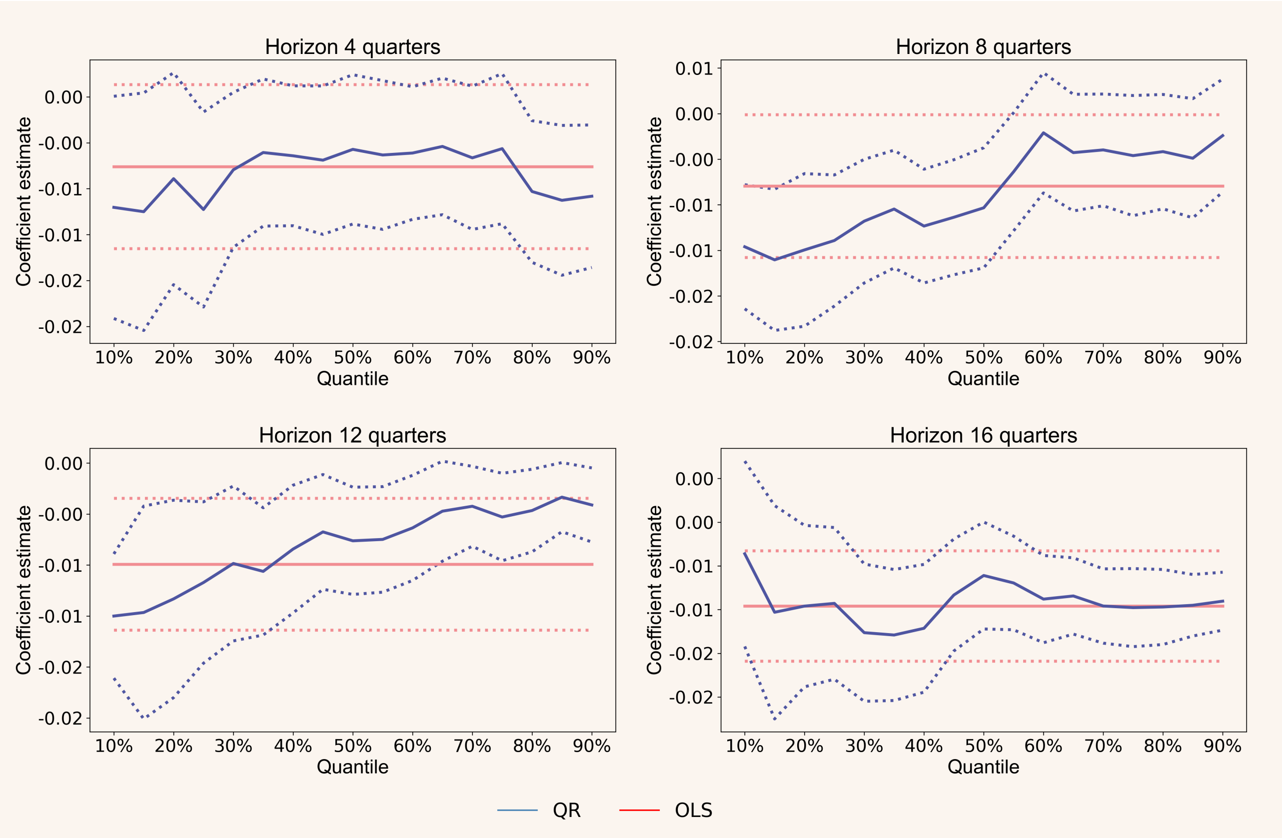

Figure 11: Quantile and OLS regression coefficients for household real debt trend deviation. In each plot, the LHS variable in regressions is average future GDP growth from time t to $t + h$, where h is the given horizon. Control variables include Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, their first lags, and first lag of the debt variable. We also include a dummy variable for time range 1999Q1-2019Q4. Dotted lines denote 95% confidence intervals: for QR standard errors are as in Greene (2008), for OLS HAC standard errors with 1 lag and small-sample correction. Time sample runs from 1980 to 2019. Quantiles are shown for interval [10%, 90%] with 5 percentage point increments.

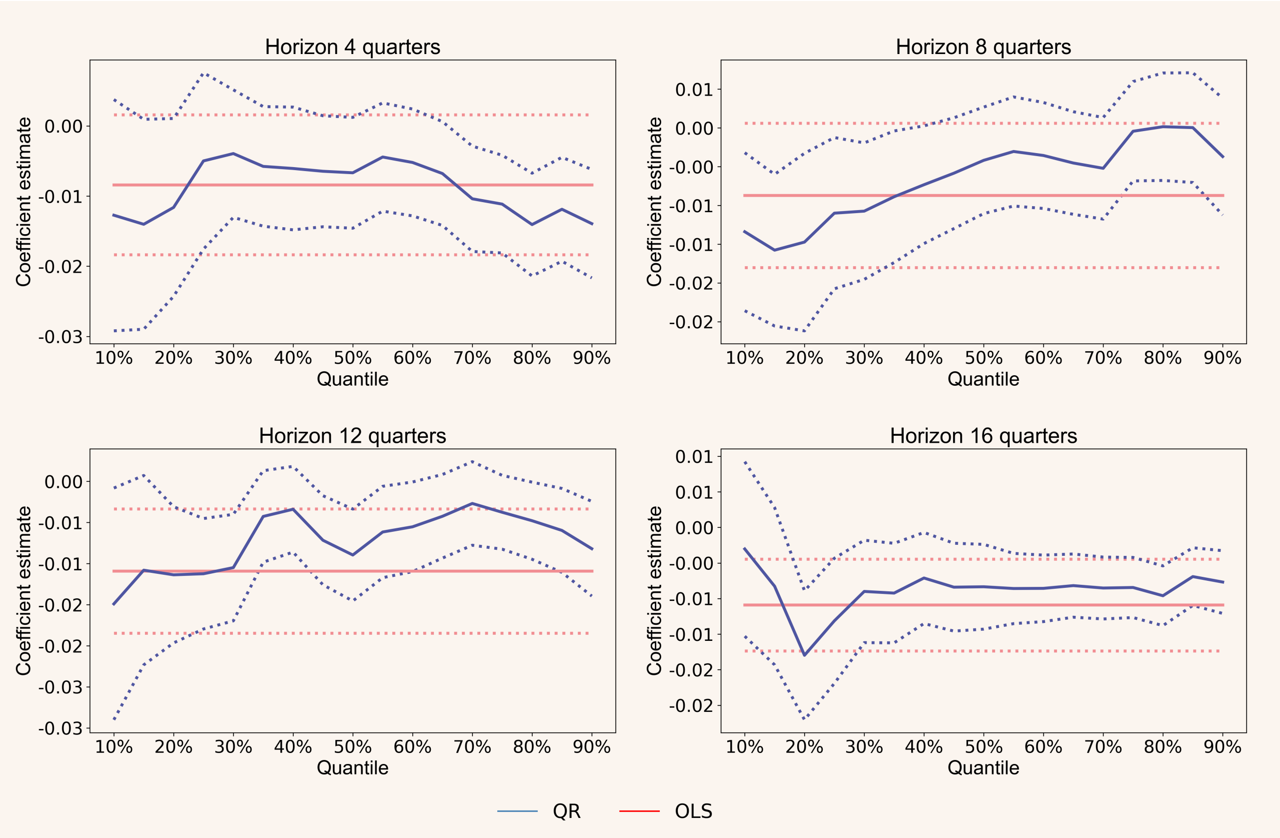

Figure 12: Quantile and OLS regression coefficients for household real debt trend deviation. In each plot, the LHS variable in regressions is average future GDP growth from time t to $t+h$, where h is the given horizon. Control variables include Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, their first lags, and first lag of the debt variable. We also include an interaction term dummy variable (range 1989Q1-2019Q4) times new mortgages interest rate. Dotted lines denote 95% confidence intervals: for QR standard errors are as in Greene (2008), for OLS HAC standard errors with 1 lag and small-sample correction. Time sample runs from 1980 to 2019. Quantiles are shown for interval [10%, 90%] with 5 percentage point increments.

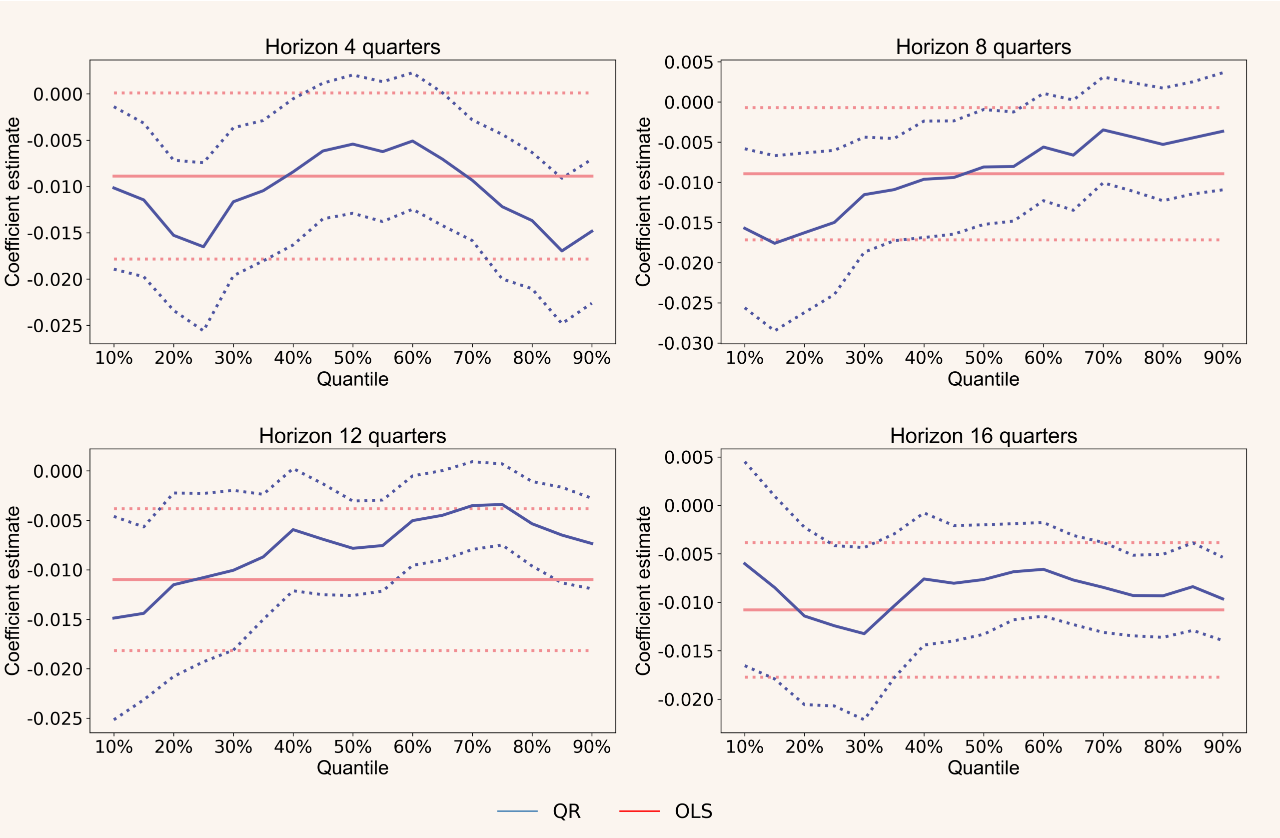

Figure 13: Quantile and OLS regression coefficients for household real debt trend deviation. In each plot, the LHS variable in regressions is average future GDP growth from time t to $t + h$, where h is the given horizon. Control variables include Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, their first lags, and first lag of the debt variable. We also include an interaction term dummy variable (range 1999Q1-2019Q4) times Euribor rate. Dotted lines denote 95% confidence intervals: for QR standard errors are as in Greene (2008), for OLS HAC standard errors with 1 lag and small-sample correction. Time sample runs from 1980 to 2019. Quantiles are shown for interval [10%, 90%] with 5 percentage point increments.

		q=0.2				q=0.5				q=0.8			
		h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16
Intercept	coef	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
	p	10%	30%	7%	13%	3%	9%	3%	1%	0%	0%	0%	0%
HH cred.	coef	-0.01	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.00	-0.00	-0.01
	p	8%	0%	0%	0%	11%	8%	10%	1%	0%	52%	5%	0%
GDP	coef	0.16	0.15	0.15	0.14	0.12	0.13	0.12	0.10	0.03	0.00	0.03	0.03
	p	2%	1%	0%	1%	1%	0%	0%	0%	48%	98%	20%	18%
HP	coef	0.03	-0.02	-0.09	-0.10	0.06	0.02	-0.00	-0.02	0.06	0.04	0.01	0.01
	p	53%	51%	0%	0%	2%	42%	80%	28%	1%	9%	51%	52%
Mort. int.	coef	-0.90	-0.58	-0.77	-0.64	-0.21	-0.55	-0.43	-0.30	0.35	-0.20	0.01	0.11
	p	0%	0%	0%	0%	25%	0%	0%	2%	6%	20%	92%	22%
Euribor	coef	0.01	-0.02	0.02	-0.06	-0.08	-0.03	-0.02	0.01	-0.16	-0.04	-0.00	-0.06
	p	92%	72%	72%	34%	24%	61%	67%	78%	2%	50%	99%	6%
CPI	coef	-0.13	-0.03	-0.21	-0.11	-0.07	0.04	0.15	0.07	-0.17	-0.09	-0.02	-0.10
	p	48%	78%	4%	34%	54%	67%	6%	38%	9%	29%	80%	8%
HH inc	coef	0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	p	95%	48%	89%	53%	37%	36%	93%	53%	13%	62%	60%	39%
HH cred., L1	coef	-0.00	-0.00	-0.00	0.00	-0.00	-0.01	-0.01	-0.00	0.01	-0.00	-0.01	0.00
	p	84%	49%	60%	46%	82%	19%	0%	53%	5%	23%	1%	65%
GDP, L1	coef	0.13	0.03	0.11	-0.04	0.08	0.09	0.06	0.02	0.06	0.07	0.02	0.06
	p	3%	55%	0%	36%	8%	2%	6%	50%	5%	6%	29%	5%
HP, L1	coef	0.12	0.04	-0.00	0.01	0.10	0.01	-0.01	0.01	0.12	0.04	0.03	0.04
	p	1%	23%	91%	63%	0%	59%	60%	80%	0%	9%	11%	1%
Mort. int., L1	coef	0.87	0.54	0.67	0.56	0.26	0.57	0.45	0.31	-0.22	0.28	0.09	0.01
	p	0%	0%	0%	0%	14%	0%	0%	1%	21%	7%	46%	91%
Euribor, L1	coef	0.02	0.09	0.08	0.13	0.06	0.05	0.04	0.02	0.11	0.03	-0.02	0.04
	p	81%	11%	16%	2%	38%	47%	42%	67%	12%	65%	73%	28%
CPI, L1	coef	0.14	-0.03	0.02	0.00	0.04	-0.10	-0.13	-0.11	0.04	-0.02	-0.06	0.05
	p	35%	72%	81%	98%	65%	27%	7%	10%	72%	82%	27%	35%
HH inc, L1	coef	0.00	-0.00	0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00	-0.00
	p	57%	85%	16%	51%	90%	18%	14%	96%	60%	89%	80%	55%

Table 1: Quantile regression coefficients and p-values for regressions with quantiles 20%, 50%, and 80%, as well as 4-, 8-, 12-, and 16-quarter horizons. Specification is the same as in Figure 4, i.e. the LHS variable in each regression is the average future GDP growth from time t to $t+h$, where h is the given horizon. The RHS variables include household real debt trend deviation, Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, and their first lags. p-values are calculated from asymptotic QR standard errors as in Greene (2008).

		q=0.2				q=0.5				q=0.8			
		h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16
Intercept	coef	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
	p	9%	30%	12%	13%	3%	7%	5%	0%	0%	0%	0%	0%
HH cred.	coef	-0.01	-0.02	-0.01	-0.01	-0.01	-0.01	-0.00	-0.01	-0.01	-0.00	-0.01	-0.01
	p	7%	0%	2%	0%	10%	7%	11%	2%	1%	40%	0%	0%
GDP	coef	0.17	0.16	0.15	0.15	0.09	0.11	0.12	0.10	0.01	-0.02	0.04	0.03
	p	1%	0%	0%	1%	6%	1%	0%	0%	80%	62%	14%	13%
Non-fin comp. cred.	coef	-0.00	0.00	-0.00	0.00	0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00
	p	92%	27%	92%	51%	59%	83%	85%	78%	37%	31%	46%	76%
HP	coef	0.03	-0.02	-0.09	-0.11	0.08	0.04	-0.00	-0.03	0.05	0.03	0.01	0.01
	p	53%	55%	0%	0%	0%	12%	88%	17%	2%	16%	78%	36%
Mort. int.	coef	-0.91	-0.72	-0.77	-0.75	-0.14	-0.39	-0.43	-0.22	0.41	-0.10	-0.01	0.06
	p	0%	0%	0%	0%	44%	2%	0%	7%	3%	55%	94%	52%
Euribor	coef	0.01	-0.06	0.03	-0.05	-0.09	-0.04	-0.02	0.01	-0.18	-0.05	-0.01	-0.05
	p	96%	32%	64%	42%	19%	47%	60%	77%	1%	37%	86%	14%
CPI	coef	-0.13	-0.08	-0.21	-0.11	-0.09	0.03	0.15	0.07	-0.19	-0.17	-0.08	-0.08
	p	47%	55%	7%	33%	39%	75%	4%	38%	6%	5%	27%	22%
HH inc	coef	0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	-0.00
	p	94%	42%	88%	92%	19%	7%	97%	52%	15%	77%	98%	22%
HH cred., L1	coef	-0.00	-0.00	-0.00	0.00	0.00	-0.01	-0.01	-0.00	0.01	-0.00	-0.00	0.00
	p	94%	59%	65%	55%	99%	18%	0%	30%	16%	20%	36%	50%
GDP, L1	coef	0.13	0.06	0.11	-0.01	0.05	0.07	0.06	0.02	0.04	0.03	0.03	0.06
	p	4%	22%	1%	85%	24%	8%	5%	40%	44%	39%	29%	6%
Non-fin comp. cred., L1	coef	-0.00	-0.00	0.00	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.00
	p	94%	69%	65%	97%	76%	74%	92%	81%	70%	81%	66%	47%
HP, L1	coef	0.12	0.05	0.00	0.03	0.11	0.01	-0.01	-0.00	0.13	0.04	0.03	0.04
	p	2%	10%	98%	34%	0%	73%	70%	97%	0%	9%	13%	3%
Mort. int., L1	coef	0.88	0.66	0.67	0.65	0.20	0.41	0.45	0.23	-0.27	0.21	0.11	0.05
	p	0%	0%	0%	0%	26%	1%	0%	5%	14%	21%	45%	56%
Euribor, L1	coef	0.02	0.13	0.07	0.13	0.07	0.06	0.04	0.02	0.12	0.03	-0.00	0.03
	p	80%	2%	26%	2%	31%	32%	38%	62%	6%	64%	98%	35%
CPI, L1	coef	0.15	0.10	0.02	0.07	0.03	-0.11	-0.13	-0.09	0.06	0.02	-0.02	0.01
	p	34%	33%	80%	48%	74%	21%	5%	15%	55%	79%	72%	90%
HH inc, L1	coef	0.00	0.00	0.00	-0.00	-0.00	0.00	0.00	0.00	-0.00	0.00	-0.00	-0.00
	p	61%	93%	44%	66%	37%	18%	13%	89%	66%	63%	75%	49%

Table 2: Quantile regression coefficients and p-values for regressions with quantiles 20%, 50%, and 80%, as well as 4-, 8-, 12-, and 16-quarter horizons. Specification is the same as in Figure 5, i.e. the LHS variable in each regression is the average future GDP growth from time t to $t+h$, where h is the given horizon. The RHS variables include household real debt trend deviation, Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, trend deviaton of real non-financial corporate debt, and their first lags. p-values are calculated from asymptotic QR standard errors as in Greene (2008).

		q=0.2				q=0.5				q=0.8			
		h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16
Intercept	coef	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
	p	22%	62%	2%	53%	0%	1%	0%	0%	0%	0%	0%	0%
HH cred/inc	coef	-0.06	-0.07	-0.04	-0.05	-0.03	-0.03	-0.03	-0.03	-0.05	-0.04	-0.02	-0.04
	p	5%	0%	3%	1%	7%	6%	1%	1%	0%	1%	5%	0%
GDP	coef	0.16	0.05	0.10	0.14	0.09	0.08	0.11	0.08	0.00	-0.04	0.02	0.02
	p	2%	26%	3%	1%	4%	4%	0%	2%	95%	28%	46%	31%
HP	coef	0.07	0.03	-0.05	-0.10	0.06	0.04	0.00	-0.01	0.06	0.03	0.01	0.01
	p	10%	26%	4%	0%	2%	6%	89%	45%	1%	16%	64%	66%
Mort. int.	coef	-0.79	-0.49	-0.62	-0.46	-0.18	-0.53	-0.44	-0.23	0.35	-0.18	0.03	0.06
	p	0%	0%	0%	1%	29%	0%	0%	6%	6%	26%	78%	60%
Euribor	coef	0.00	0.03	0.04	-0.08	-0.05	0.00	0.02	0.06	-0.17	-0.01	-0.02	-0.02
	p	96%	58%	34%	16%	44%	99%	64%	23%	1%	85%	68%	67%
CPI	coef	-0.16	-0.31	-0.09	-0.13	-0.04	0.11	0.14	0.11	-0.20	-0.16	-0.02	-0.06
	p	36%	1%	36%	21%	74%	25%	6%	15%	4%	9%	75%	32%
HH inc	coef	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	p	22%	0%	7%	1%	2%	2%	3%	0%	0%	1%	7%	0%
HH cred/inc., L1	coef	0.00	-0.01	-0.02	0.00	-0.01	-0.03	-0.04	-0.02	0.03	0.01	-0.03	-0.00
	p	91%	80%	26%	90%	47%	3%	0%	12%	13%	59%	0%	77%
GDP, L1	coef	0.10	0.02	0.09	-0.02	0.07	0.07	0.07	0.01	0.07	0.04	0.04	0.05
	p	8%	58%	2%	64%	9%	6%	2%	66%	12%	18%	10%	2%
HP, L1	coef	0.13	0.07	0.00	0.03	0.09	-0.00	-0.03	-0.01	0.13	0.06	0.02	0.04
	p	0%	3%	86%	28%	0%	84%	16%	59%	0%	2%	15%	2%
Mort. int., L1	coef	0.74	0.46	0.55	0.48	0.22	0.54	0.43	0.26	-0.21	0.28	0.07	0.04
	p	0%	0%	0%	0%	20%	0%	0%	3%	25%	9%	48%	71%
Euribor, L1	coef	0.03	0.05	0.03	0.07	0.04	0.01	0.00	-0.04	0.11	-0.01	-0.01	0.00
	p	69%	36%	56%	16%	56%	87%	96%	43%	10%	83%	90%	97%
CPI, L1	coef	0.17	-0.09	-0.05	0.06	0.02	-0.08	-0.07	-0.13	0.08	0.06	0.02	0.04
	p	24%	28%	48%	48%	83%	30%	30%	6%	45%	45%	68%	41%
HH inc, L1	coef	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00
	p	92%	50%	46%	99%	53%	24%	6%	22%	27%	57%	3%	94%

Table 3: Quantile regression coefficients and p-values for regressions with quantiles 20%, 50%, and 80%, as well as 4-, 8-, 12-, and 16-quarter horizons. Specification is the same as in Figure 7, i.e. the LHS variable in each regression is the average future GDP growth from time t to $t+h$, where h is the given horizon. The RHS variables include household debt-to-income trend deviation, Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, and their first lags. p-values are calculated from asymptotic QR standard errors as in Greene (2008).

		q=0.2				q=0.5				q=0.8			
		h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16
Intercept	coef	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
	p	19%	26%	7%	29%	6%	2%	0%	1%	0%	0%	0%	0%
HH cred.	coef	-0.01	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.00	-0.00	-0.01
	p	11%	0%	0%	0%	14%	11%	3%	2%	0%	27%	28%	0%
GDP	coef	0.13	0.12	0.13	0.16	0.14	0.13	0.13	0.11	0.07	0.02	0.03	0.05
	p	4%	2%	1%	0%	0%	0%	0%	0%	6%	49%	24%	7%
HP	coef	0.03	-0.01	-0.08	-0.12	0.07	0.03	0.00	-0.02	0.06	0.04	0.02	0.02
	p	40%	70%	0%	0%	2%	21%	93%	38%	0%	5%	37%	24%
Mort. int.	coef	-0.78	-0.61	-0.66	-0.57	-0.29	-0.49	-0.42	-0.34	0.16	-0.18	-0.01	0.09
	p	0%	0%	0%	0%	12%	0%	0%	0%	34%	24%	91%	42%
Euribor	coef	0.00	-0.05	0.02	-0.06	-0.07	-0.03	-0.02	0.00	-0.06	-0.05	-0.00	-0.04
	p	99%	36%	70%	38%	34%	58%	65%	95%	35%	40%	98%	16%
CPI	coef	-0.09	-0.08	-0.24	-0.15	-0.04	0.06	0.14	0.08	-0.20	-0.15	-0.02	-0.09
	p	58%	52%	2%	21%	74%	56%	6%	28%	4%	10%	81%	10%
HH inc	coef	-0.01	0.03	-0.00	-0.01	-0.01	-0.04	-0.01	-0.01	-0.04	-0.03	-0.02	-0.02
	p	83%	34%	82%	72%	77%	10%	39%	61%	9%	13%	19%	10%
HH cred., L1	coef	-0.01	-0.00	-0.00	0.00	-0.00	-0.01	-0.01	-0.00	0.01	-0.00	-0.01	0.00
	p	47%	66%	71%	67%	72%	11%	3%	39%	2%	70%	0%	45%
GDP, L1	coef	0.15	0.03	0.09	-0.01	0.10	0.09	0.06	0.04	0.06	0.07	0.03	0.06
	p	1%	56%	3%	86%	2%	3%	4%	20%	6%	5%	16%	5%
HP, L1	coef	0.10	0.05	0.01	0.03	0.09	0.00	-0.01	-0.00	0.13	0.06	0.03	0.04
	p	0%	10%	84%	37%	0%	88%	69%	83%	0%	1%	8%	2%
Mort. int., L1	coef	0.74	0.55	0.56	0.53	0.33	0.50	0.43	0.36	-0.07	0.26	0.12	0.02
	p	0%	0%	0%	0%	6%	0%	0%	0%	66%	9%	28%	81%
Euribor, L1	coef	0.04	0.12	0.08	0.10	0.05	0.06	0.04	0.03	0.05	0.05	-0.02	0.03
	p	66%	3%	17%	8%	53%	36%	37%	51%	52%	39%	71%	38%
CPI, L1	coef	0.06	0.01	0.02	-0.02	0.06	-0.13	-0.13	-0.12	-0.03	-0.04	-0.06	-0.00
	p	65%	95%	82%	84%	54%	16%	6%	8%	74%	65%	28%	94%
HH inc, L1	coef	0.03	0.03	0.01	-0.02	0.02	-0.03	0.00	-0.01	-0.04	-0.03	-0.02	-0.02
	p	53%	38%	69%	61%	53%	24%	82%	75%	11%	12%	10%	16%

Table 4: Quantile regression coefficients and p-values for regressions with quantiles 20%, 50%, and 80%, as well as 4-, 8-, 12-, and 16-quarter horizons. Specification is the same as in Figure 8, i.e. the LHS variable in each regression is the average future GDP growth from time t to $t{+}h$, where h is the given horizon. The RHS variables include household real debt trend deviation, Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, Q-o-Q household real income growth, and their 1st lags. p-values are calculated from asymptotic QR standard errors as in Greene (2008).

		1975-2019			1994-2019			1975-2007			1975-1989		
		q=0.2	q=0.5	q=0.8	q=0.2	q=0.5	q=0.8	q=0.2	q=0.5	q=0.8	q=0.2	q=0.5	q=0.8
Intercept	coef	-0.00	0.00	0.01	-0.00	-0.00	0.00	-0.00	0.00	0.02	0.03	0.05	0.04
	p	84%	2%	0%	0%	3%	47%	29%	2%	0%	0%	0%	0%
HH cred.	coef	-0.02	-0.01	-0.01	-0.00	0.00	0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	p	0%	4%	14%	59%	70%	5%	4%	6%	2%	0%	0%	12%
GDP	coef	0.07	0.06	-0.02	-0.07	-0.03	-0.07	0.14	0.03	-0.11	-0.11	-0.18	-0.17
	p	19%	11%	59%	7%	38%	15%	3%	53%	1%	5%	0%	0%
HP	coef	0.01	0.04	0.04	0.04	0.01	0.11	-0.02	0.02	0.01	0.04	0.05	0.04
	p	83%	10%	6%	27%	64%	0%	64%	42%	72%	11%	0%	9%
Mort. int.	coef	-0.43	-0.43	-0.25	0.52	0.32	0.71	-0.56	-0.43	-0.35	-0.18	-0.15	-0.17
	p	0%	0%	14%	18%	25%	5%	0%	1%	5%	31%	15%	24%
Euribor	coef	-0.03	0.01	-0.03	-0.35	-0.26	-0.12	0.05	0.00	0.02	-0.01	0.03	0.01
	p	25%	63%	54%	18%	18%	58%	8%	99%	64%	53%	2%	52%
CPI	coef	-0.22	0.01	-0.21	-0.24	-0.34	-0.26	0.06	0.11	-0.15	-0.17	-0.29	-0.18
	p	5%	96%	2%	4%	0%	2%	62%	31%	19%	11%	0%	25%
HH inc	coef	-0.00	-0.00	-0.00	0.00	0.00	-0.00	0.00	-0.00	0.00	0.00	-0.00	-0.00
	p	76%	4%	41%	64%	61%	45%	36%	1%	78%	61%	28%	47%
HH cred., L1	coef	-0.00	-0.00	0.00	-0.01	-0.00	-0.01	-0.01	-0.01	-0.01	-0.00	-0.00	-0.01
	p	70%	24%	95%	2%	12%	2%	43%	19%	35%	44%	72%	20%
GDP, L1	coef	0.00	0.05	0.03	-0.03	0.00	-0.03	0.09	0.05	-0.00	-0.08	-0.16	-0.04
	p	96%	14%	34%	42%	99%	44%	14%	30%	93%	13%	0%	36%
HP, L1	coef	0.06	0.01	0.06	0.06	0.05	0.00	0.02	-0.02	-0.01	0.01	0.04	0.01
	p	8%	58%	1%	12%	7%	92%	63%	50%	78%	84%	2%	73%
Mort. int., L1	coef	0.40	0.44	0.30	0.12	0.30	-0.22	0.56	0.43	0.26	-0.05	-0.25	-0.13
	p	0%	0%	8%	74%	24%	48%	0%	1%	17%	77%	3%	49%
Euribor, L1	coef	0.11	0.02	0.06	-0.23	-0.30	-0.24	-0.03	0.01	0.00	0.04	-0.01	0.00
	p	0%	53%	18%	30%	10%	23%	18%	62%	96%	1%	64%	89%
CPI, L1	coef	-0.13	-0.07	-0.04	-0.20	-0.12	-0.26	0.03	-0.10	0.00	-0.19	-0.10	-0.05
	p	18%	38%	64%	5%	14%	2%	77%	30%	97%	6%	7%	52%
HH inc, L1	coef	-0.00	0.00	-0.00	0.00	0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00
	p	40%	50%	66%	40%	4%	66%	87%	25%	84%	21%	100%	70%

Table 5: Quantile regression coefficients and p-values for regressions with varying sample sizes. Coefficients are shown for quantiles 20%, 50%, and 80%, with 8-quarter horizon. Specification is the same as in Figure 9, i.e. the LHS variable in each regression is the average future GDP growth from time t to $t{+}h$, where $h = 8$. RHS variables include household real debt trend deviation, Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, and their first lags. p-values are calculated from asymptotic QR standard errors as in Greene (2008).

		q=0.2				q=0.5				q=0.8			
		h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16
Intercept	coef	0.01	0.01	0.01	-0.00	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.00
	p	5%	1%	15%	24%	0%	0%	0%	45%	0%	0%	4%	24%
HH cred.	coef	-0.01	-0.01	-0.01	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.00	-0.00	-0.01
	p	14%	1%	2%	0%	6%	16%	0%	1%	0%	42%	5%	0%
GDP	coef	0.12	0.08	0.11	0.20	0.12	0.13	0.12	0.09	0.00	-0.01	0.04	0.03
	p	8%	10%	3%	0%	1%	0%	0%	0%	98%	68%	18%	14%
HP	coef	-0.01	-0.03	-0.08	-0.09	0.05	0.00	-0.02	-0.02	0.05	0.04	0.01	0.01
	p	88%	31%	1%	0%	6%	89%	25%	43%	8%	10%	60%	53%
Mort. int.	coef	-0.77	-0.51	-0.64	-0.80	-0.23	-0.63	-0.46	-0.29	0.46	-0.09	0.02	0.10
	p	0%	0%	0%	0%	18%	0%	0%	2%	1%	54%	89%	26%
Euribor	coef	-0.09	-0.05	0.02	0.10	-0.13	-0.05	-0.01	0.02	-0.20	-0.09	-0.01	-0.06
	p	36%	40%	72%	13%	6%	42%	86%	73%	0%	11%	88%	9%
CPI	coef	-0.35	-0.20	-0.19	-0.05	-0.07	0.03	0.07	0.06	-0.27	-0.09	-0.02	-0.10
	p	2%	12%	8%	70%	52%	79%	33%	42%	0%	32%	71%	8%
HH inc	coef	0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	p	20%	76%	76%	66%	8%	71%	90%	45%	5%	73%	51%	31%
HH cred., L1	coef	-0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00	0.01	-0.00	-0.01	0.00
	p	91%	84%	48%	45%	64%	27%	29%	56%	0%	65%	1%	57%
GDP, L1	coef	0.20	0.05	0.10	-0.02	0.05	0.10	0.06	0.02	0.05	0.06	0.02	0.06
	p	0%	16%	1%	56%	19%	1%	4%	46%	18%	8%	34%	1%
HP, L1	coef	0.10	0.04	-0.00	0.02	0.09	-0.00	0.01	0.01	0.12	0.04	0.03	0.04
	p	2%	20%	96%	58%	0%	98%	71%	70%	0%	11%	9%	1%
Mort. int., L1	coef	0.77	0.48	0.53	0.68	0.34	0.72	0.51	0.31	-0.28	0.25	0.09	0.01
	p	0%	0%	0%	0%	4%	0%	0%	1%	11%	9%	44%	86%
Euribor, L1	coef	0.05	0.07	0.06	0.03	0.02	-0.02	-0.02	0.02	0.08	0.00	-0.02	0.04
	p	62%	33%	32%	65%	72%	77%	64%	69%	20%	98%	73%	23%
CPI, L1	coef	0.11	-0.03	-0.01	0.02	-0.05	-0.19	-0.12	-0.10	0.01	-0.02	-0.05	0.05
	p	37%	78%	91%	87%	60%	3%	6%	13%	91%	80%	33%	32%
HH inc, L1	coef	0.00	0.00	0.00	-0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00	-0.00
	p	52%	65%	60%	71%	82%	66%	20%	91%	51%	80%	70%	54%
dummy	coef	-0.01	-0.01	-0.00	0.01	-0.01	-0.01	-0.01	0.00	-0.01	-0.00	-0.00	0.00
	p	4%	2%	54%	14%	0%	0%	1%	85%	0%	7%	71%	75%

Table 6: Quantile regression coefficients and p-values for regressions with quantiles 20%, 50%, and 80%, as well as 4-, 8-, 12-, and 16-quarter horizons. Specification is the same as in Figure 10, i.e. the LHS variable in each regression is the average future GDP growth from time t to $t+h$, where h is the given horizon. The RHS variables include household real debt trend deviation, Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, and their first lags. We also include a dummy variable for time range 1989Q1-2019Q4. p-values are calculated from asymptotic QR standard errors as in Greene (2008).

		q=0.2				q=0.5				q=0.8			
		h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16
Intercept	coef	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01
	p	0%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%
HH cred.	coef	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.00	-0.00	-0.01
	p	13%	0%	1%	4%	17%	0%	0%	5%	1%	19%	2%	0%
GDP	coef	0.12	0.07	0.10	0.12	0.07	0.01	0.07	0.07	0.02	-0.00	0.03	0.04
	p	6%	14%	3%	1%	9%	69%	2%	3%	70%	93%	22%	9%
HP	coef	0.04	0.01	-0.06	-0.09	0.06	0.02	-0.02	-0.03	0.06	0.03	0.00	0.00
	p	23%	69%	2%	0%	1%	27%	13%	11%	1%	7%	94%	81%
Mort. int.	coef	-0.74	-0.43	-0.57	-0.81	-0.27	-0.50	-0.37	-0.29	0.41	-0.13	-0.06	0.07
	p	0%	0%	0%	0%	11%	0%	0%	2%	3%	36%	67%	52%
Euribor	coef	-0.04	-0.07	0.01	0.01	-0.06	-0.02	-0.01	0.02	-0.18	-0.06	-0.01	-0.05
	p	65%	16%	87%	86%	33%	72%	80%	73%	1%	26%	79%	16%
CPI	coef	-0.20	-0.18	-0.19	-0.09	-0.14	0.02	0.07	0.04	-0.14	-0.16	-0.04	-0.10
	p	16%	7%	9%	42%	17%	82%	28%	62%	15%	6%	59%	12%
HH inc	coef	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	p	45%	38%	8%	57%	3%	66%	27%	53%	39%	56%	95%	54%
HH cred., L1	coef	-0.00	0.00	-0.00	0.00	-0.00	-0.01	-0.00	-0.00	0.01	-0.00	-0.00	0.00
	p	60%	95%	97%	61%	98%	15%	11%	34%	8%	69%	4%	38%
GDP, L1	coef	0.11	-0.02	0.07	-0.03	0.05	0.03	0.04	0.02	0.06	0.04	0.03	0.05
	p	1%	57%	8%	44%	25%	41%	11%	57%	10%	21%	15%	14%
HP, L1	coef	0.08	0.05	-0.01	-0.03	0.09	-0.01	-0.01	-0.01	0.13	0.05	0.02	0.04
	p	1%	5%	82%	24%	0%	56%	61%	73%	0%	2%	35%	3%
Mort. int., L1	coef	0.54	0.26	0.41	0.62	0.20	0.39	0.32	0.24	-0.29	0.17	0.10	-0.01
	p	1%	5%	1%	0%	22%	0%	0%	5%	12%	26%	46%	93%
Euribor, L1	coef	0.10	0.15	0.08	0.07	0.08	0.05	0.03	0.02	0.11	0.04	-0.02	0.03
	p	19%	0%	19%	14%	24%	37%	48%	74%	14%	42%	62%	42%
CPI, L1	coef	0.06	-0.15	-0.05	0.01	-0.01	-0.09	-0.12	-0.09	0.02	-0.05	-0.06	0.01
	p	56%	5%	55%	89%	94%	20%	5%	19%	85%	49%	31%	92%
HH inc, L1	coef	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	-0.00	-0.00	0.00	0.00	0.00
	p	85%	66%	70%	8%	78%	59%	90%	63%	81%	2%	4%	35%
dummy	coef	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.00	-0.01	-0.01	-0.00
	p	0%	0%	0%	0%	0%	0%	0%	0%	26%	0%	0%	1%

Table 7: Quantile regression coefficients and p-values for regressions with quantiles 20%, 50%, and 80%, as well as 4-, 8-, 12-, and 16-quarter horizons. Specification is the same as in Figure 11, i.e. the LHS variable in each regression is the average future GDP growth from time t to $t+h$, where h is the given horizon. The RHS variables include household real debt trend deviation, Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, and their first lags. We also include a dummy variable for time range 1999Q1-2019Q4. p-values are calculated from asymptotic QR standard errors as in Greene (2008).

		q=0.2				q=0.5				q=0.8			
		h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16
Intercept	coef	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
	p	56%	25%	11%	65%	3%	1%	0%	2%	0%	0%	0%	0%
HH cred.	coef	-0.01	-0.01	-0.01	-0.02	-0.01	-0.00	-0.01	-0.01	-0.01	0.00	-0.00	-0.01
	p	7%	1%	1%	0%	10%	23%	0%	1%	0%	97%	5%	0%
GDP	coef	0.14	0.08	0.12	0.20	0.10	0.13	0.13	0.10	0.02	-0.01	0.06	0.04
	p	4%	7%	1%	0%	2%	0%	0%	0%	56%	77%	0%	5%
Interaction	coef	-0.05	-0.03	-0.05	0.06	-0.18	-0.17	-0.12	-0.12	-0.23	-0.28	-0.21	-0.21
	p	42%	49%	19%	20%	0%	0%	0%	1%	0%	0%	0%	0%
HP	coef	-0.01	-0.01	-0.08	-0.08	0.06	0.02	-0.02	-0.01	0.05	0.03	-0.00	0.01
	p	75%	60%	0%	0%	2%	45%	32%	45%	6%	24%	100%	62%
Mort. int.	coef	-0.80	-0.54	-0.67	-0.82	-0.02	-0.46	-0.35	-0.23	0.57	0.16	0.11	0.18
	p	0%	0%	0%	0%	93%	0%	0%	7%	0%	33%	28%	12%
Euribor	coef	-0.07	-0.02	-0.03	0.10	-0.11	-0.09	-0.01	0.01	-0.19	-0.10	-0.01	-0.04
	p	47%	73%	63%	13%	8%	13%	80%	76%	0%	6%	87%	33%
CPI	coef	-0.39	-0.21	-0.20	-0.05	-0.07	0.08	0.09	0.07	-0.23	-0.11	-0.05	-0.11
	p	1%	9%	4%	67%	52%	35%	19%	35%	2%	19%	43%	6%
HH inc	coef	0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	p	17%	70%	99%	72%	6%	56%	78%	38%	7%	42%	74%	49%
HH cred., L1	coef	0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00	0.01	-0.00	-0.00	0.00
	p	89%	82%	69%	42%	69%	21%	16%	62%	0%	30%	24%	26%
GDP, L1	coef	0.19	0.04	0.12	-0.03	0.05	0.09	0.05	0.02	0.06	0.07	0.03	0.07
	p	0%	30%	0%	48%	18%	1%	10%	45%	12%	6%	23%	1%
Interaction, L1	coef	-0.05	-0.03	0.04	0.00	0.10	0.11	0.09	0.13	0.18	0.24	0.20	0.23
	p	38%	46%	26%	98%	10%	3%	3%	0%	0%	1%	0%	0%
HP, L1	coef	0.10	0.03	0.04	0.01	0.11	0.01	0.01	0.01	0.12	0.05	0.04	0.04
	p	1%	40%	17%	71%	0%	76%	45%	61%	0%	6%	2%	1%
Mort. int., L1	coef	0.90	0.54	0.61	0.64	0.22	0.57	0.42	0.22	-0.36	0.02	0.02	-0.11
	p	0%	0%	0%	0%	18%	0%	0%	6%	3%	90%	83%	31%
Euribor, L1	coef	0.03	0.06	0.10	0.04	0.01	0.05	0.00	0.03	0.09	0.04	-0.03	0.04
	p	75%	38%	8%	56%	94%	37%	96%	54%	17%	55%	57%	34%
CPI, L1	coef	0.17	0.01	-0.03	0.02	-0.02	-0.20	-0.13	-0.10	0.06	-0.02	-0.03	0.07
	p	16%	94%	68%	83%	84%	1%	4%	14%	49%	85%	63%	15%
HH inc, L1	coef	0.00	0.00	0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	p	46%	61%	50%	72%	80%	66%	21%	94%	59%	80%	86%	25%

Table 8: Quantile regression coefficients and p-values for regressions with quantiles 20%, 50%, and 80%, as well as 4-, 8-, 12-, and 16-quarter horizons. Specification is the same as in Figure 12, i.e. the LHS variable in each regression is the average future GDP growth from time t to $t+h$, where h is the given horizon. The RHS variables include household real debt trend deviation, Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, and their first lags. We also include an interaction term, dummy variable (range 1989Q1-2019Q4) times new mortgages interest rate. p-values are calculated from asymptotic QR standard errors as in Greene (2008).

		q=0.2				q=0.5				q=0.8			
		h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16
Intercept	coef	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00
	p	1%	17%	3%	8%	0%	0%	0%	0%	0%	0%	0%	0%
HH cred.	coef	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	p	0%	0%	2%	2%	15%	3%	0%	1%	0%	14%	2%	0%
GDP	coef	0.13	0.14	0.09	0.10	0.06	0.06	0.08	0.09	-0.00	-0.06	0.02	0.01
	p	2%	0%	4%	7%	17%	10%	0%	0%	99%	14%	27%	84%
Interaction	coef	0.03	0.17	0.34	0.38	0.45	0.11	-0.01	0.14	0.37	0.51	-0.00	0.11
	p	91%	43%	10%	15%	0%	38%	91%	16%	0%	0%	96%	8%
HP	coef	0.05	-0.01	-0.03	-0.12	0.10	0.04	-0.01	-0.02	0.07	0.05	0.02	0.02
	p	9%	85%	18%	0%	0%	10%	65%	30%	1%	2%	25%	18%
Mort. int.	coef	-0.93	-0.90	-0.83	-0.87	-0.42	-0.52	-0.31	-0.42	0.21	-0.23	0.01	0.09
	p	0%	0%	0%	0%	1%	0%	0%	0%	23%	11%	92%	35%
Euribor	coef	-0.02	-0.08	0.02	-0.03	-0.04	-0.02	-0.01	0.03	-0.11	-0.01	-0.03	-0.03
	p	73%	13%	71%	65%	54%	74%	76%	46%	7%	79%	46%	24%
CPI	coef	-0.26	-0.11	-0.15	-0.11	-0.19	0.03	0.05	0.07	-0.25	-0.17	-0.05	-0.10
	p	3%	31%	16%	35%	5%	73%	44%	30%	2%	5%	46%	9%
HH inc	coef	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	p	43%	49%	34%	3%	1%	42%	67%	33%	1%	9%	42%	3%
HH cred., L1	coef	0.00	0.00	-0.00	0.00	-0.00	-0.01	-0.00	-0.00	0.01	-0.00	-0.00	0.00
	p	67%	79%	71%	52%	98%	17%	18%	52%	3%	61%	9%	38%
GDP, L1	coef	0.09	0.05	0.09	0.01	0.04	0.05	0.03	0.02	0.00	0.03	0.02	0.05
	p	2%	19%	2%	87%	24%	15%	18%	52%	98%	43%	45%	8%
Interaction, L1	coef	-0.21	-0.27	-0.37	-0.42	-0.52	-0.20	-0.06	-0.18	-0.38	-0.55	-0.05	-0.16
	p	42%	20%	9%	11%	0%	11%	45%	6%	0%	0%	42%	1%
HP, L1	coef	0.11	0.05	-0.04	0.02	0.09	0.00	0.01	0.01	0.13	0.05	0.04	0.03
	p	0%	11%	11%	46%	0%	97%	40%	73%	0%	2%	3%	10%
Mort. int., L1	coef	0.81	0.83	0.71	0.76	0.43	0.52	0.35	0.44	-0.12	0.31	0.12	0.01
	p	0%	0%	0%	0%	0%	0%	0%	0%	47%	3%	33%	95%
Euribor, L1	coef	0.09	0.15	0.09	0.12	0.06	0.04	0.02	-0.00	0.09	0.02	-0.01	0.02
	p	11%	0%	6%	5%	31%	44%	59%	93%	15%	76%	72%	52%
CPI, L1	coef	0.13	0.00	-0.00	-0.05	-0.02	-0.08	-0.12	-0.10	0.02	-0.03	-0.02	0.00
	p	22%	100%	100%	58%	79%	30%	3%	11%	83%	72%	63%	96%
HH inc, L1	coef	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	-0.00	-0.00	0.00	0.00	0.00
	p	87%	63%	77%	4%	70%	79%	70%	61%	87%	83%	24%	79%

Table 9: Quantile regression coefficients and p-values for regressions with quantiles 20%, 50%, and 80%, as well as 4-, 8-, 12-, and 16-quarter horizons. Specification is the same as in Figure 13, i.e. the LHS variable in each regression is the average future GDP growth from time t to $t{+}h$, where h is the given horizon. RHS variables include household real debt trend deviation, Q-o-Q real GDP growth, Q-o-Q house price growth, Euribor12, interest rate of new mortgages, Q-o-Q growth in CPI, trend deviation of household real income, and their first lags. We also include an interaction term, dummy variable (range 1999Q1-2019Q4) times Euribor rate. p-values are calculated from asymptotic QR standard errors as in Greene (2008).