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Households' Macroeconomic Conditions and Credit Dynamics

Martin Hodula, Simona Malovaná, and Jan Frait*

Abstract

We focus on the link between the macroeconomic conditions faced by households, the confidence of households as investors and consumers, and households' demand for credit. On a sample of 21 OECD countries, we provide empirical evidence that links households' macroeconomic conditions to the evolution of credit. Specifically, we find that: (i) the well-known procyclicality of credit is reinforced in periods of favorable macroeconomic conditions; (ii) the relationship in question grows stronger when good macro conditions are met with optimistic consumer confidence; (iii) household credit is sticky on the way down, while it goes hand in hand with the improving economy during an economic upturn.

Abstrakt

Zaměřujeme se na vazbu mezi makroekonomickými podmínkami domácností, důvěrou domácností coby investorů a spotřebitelů a poptávkou domácností po úvěrech. Na vzorku 21 zemí OECD empiricky dokládáme vazbu mezi makroekonomickými podmínkami domácností a vývojem úvěrů. Konkrétně zjišťujeme, že: (i) dobře známá procykličnost úvěrů je zesílena v obdobích příznivých makroekonomických podmínek; (ii) daný vztah zesiluje při souběhu příznivých makroekonomických podmínek s optimistickou spotřebitelskou důvěrou; (iii) úvěry domácnostem jsou při poklesu ekonomiky strnulé, zatímco v růstové fázi se vyvíjejí ruku v ruce se zlepšující se ekonomikou.

JEL Codes: F12, F41, F43.

Keywords: Credit, households, macroeconomic conditions, panel data.

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1. Introduction

We investigate key macroeconomic factors affecting demand for credit in the household sector which may contribute to excessive household indebtedness and the emergence of financial imbalances. The underlying dynamics of credit to households continue to be of strong interest to policymakers worldwide. This stems from the fact that a number of economies have experienced the destabilizing effects of major fluctuations in household credit and related asset prices. The experience during and after the Global Financial Crisis (GFC) was particularly costly.

The issue of households' credit dynamics can be viewed from two different perspectives. The first strand of literature is empirical and generally aims to verify potential determinants of credit dynamics from either the demand or supply side. Prominent examples of such studies are Hofmann (2004), Cottarelli et al. (2005), and Jiménez et al. (2017). The second strand of literature uses theoretical general equilibrium models to assess how various economic and institutional factors affect the evolution of credit in the economy (Huggett, 1996; Rubaszek and Serwa, 2014). Still, regardless of the approach, the literature generally agrees that macroeconomic factors have a prominent role in explaining the evolution of credit.

Our study contributes to the existing literature in at least two ways. First, we address a common problem of household credit growth models – overparameterization and overfitting. In emerging market economies in particular, the time series of loans are often too short. This puts a burden on the modeling framework, which cannot cope with too many variables. Consequently, such models often fail to deliver reliable estimates (see Geršl and Seidler, 2015). To overcome this issue, we use a composite index – the Households' Macroeconomic Conditions Index (H-MCI) – developed and described in detail in Hodula et al. (2019).

Second, we contribute to the current state of knowledge on the link between households' macroeconomic conditions, the confidence of households as investors and consumers, and household credit. One of the key factors affecting households' demand for credit is their expectations regarding future economic developments, in particular their level of optimism (or pessimism) regarding the economic outlook. We explain that households may extrapolate recent and current macroeconomic trends to the future and over-estimate the persistence of favorable or adverse conditions. We offer some econometric evidence supporting this statement. Specifically, we estimate a series of dynamic panel regressions and provide time series evidence linking a higher H-MCI to increasing household indebtedness. This relationship is fostered when favorable macroeconomic conditions are met with optimistic consumer confidence as proxied by the OECD Consumer Confidence Index (CCI). Further, we find the relationship to be stronger when macroeconomic conditions and consumer confidence are favorable. In contrast, credit to households seems to be sticky on the way down, i.e., in periods of less favorable macroeconomic conditions. Moreover, we document that the larger and longer is the boom, the more likely is the economy to end up busting.

The remainder of the paper is structured as follows. Section 2 discusses the relationship between household confidence and the evolution of credit in the existing literature. Section 3 presents the empirical framework. Section 4 discusses the results and section 5 concludes.

2. Household Confidence and the Evolution of Credit: A Review

The literature on the links between household confidence and the evolution of credit is not particularly rich. The GFC nevertheless gave a boost to interest in this topic. The majority of studies focus on the causal chain between the following variables: macroeconomic conditions perceived by households, residential real property and its prices, and (secured) housing credit. The interest in the links between macroeconomic conditions and demand for unsecured consumer loans is naturally not so strong, owing to the much lower volumes of such loans relative to housing loans. However, the two segments of household credit tend to move in tandem, since increases in housing prices driven by credit feed into demand for consumer loans through the wealth effect and equity withdrawal. The apparent coincidence of secured and unsecured credit drifts, documented, for example, by Jordà et al. (2016), thus makes the results of studies on housing credit relevant to consumer credit.

One stream of literature is focused on the determinants of credit booms associated with asset price drifts and the feedback loop between property prices and housing credit. Kiyotaki and Moore (1997) emphasize the role of collateral in these linkages. Attanasio et al. (2009) add that the effect of rising house prices on income expectations may also play a role. Goodhart and Hofmann (2008) provide empirical evidence on the existence of a link between money, property prices, and credit. Jordà et al. (2015) demonstrate that loose monetary conditions lead to booms in real estate lending and house prices; these, in turn, increase financial fragility.

Another stream of literature is focused on expectational factors contributing to credit booms while leaving aside the assumptions of rational behavior and expectations. Psychological factors are used to explain the occurrence of household overconfidence (Bao and Li, 2016; Hwang et al., 2016). Some of the recent observations on credit booms build upon the concept of extrapolative expectations, which was used in the past to explain asset price movements (Schiller, 2000; Williams, 2013, 2013a, 2014). Extrapolative expectations may even become temporarily self-fulfilling. Let us illustrate this using a simple example involving wages and income. In a situation where fast income growth is met with low interest rates, households may begin to form optimistic expectations. Should the conditions last long enough, they could be gradually extrapolated to the view that the good times will last "forever". Households could then be inclined to tolerate a much higher level of indebtedness. If these optimistic expectations are accompanied by steady growth in asset prices, the overall level of debt can shoot up in a relatively short period. This way of forming expectations is an outcome of the constrained rationality of households. Households tend to underrate the probability that a period of abnormal income growth will be followed by a subnormal one. Fuster et al. (2010) argue that households tend to have wrong beliefs about the true development of fundamental factors and over-estimate the persistence of favorable conditions. Nofsinger (2012) explains that factors such as extrapolation biases, groupthink, and cognitive limitations lead households in boom times to chase and extend asset bubbles through an increasing use of debt. In bust times, fear and political responses to the public outcry contribute to strong procyclical credit drops. Bordalo et al. (2018) present a model of credit cycles arising from diagnostic expectations in which agents tend to overweight future outcomes that they have anticipated in light of current data. Foote et al. (2012) argue that the facts refute the popular story that the GFC resulted from finance industry insiders deceiving uninformed mortgage borrowers and investors. Instead, they argue that borrowers and investors made decisions that were rational and logical given their ex post overly optimistic beliefs about the development of house prices.

A multitude of empirical studies rely on some form of consumer confidence indicator to capture households' expectations. De Stefani (2017) documents that expectations of US households contain a component of systematic extrapolative bias which is inconsistent with full-information rational expectations theory. He shows that a change in house price expectations has substantial effects on mortgage leverage, which increases whenever there is an expected increase in home equity. Angelico (2018) provides empirical evidence that survey data on expectations have strong predictive power for the dynamics of household debt. She shows that beliefs depart from rationality at the aggregate level in a way coherent with the hypothesis of natural expectations. A positive shock to income first generates a boom, since households fail to forecast long-run income and get over-indebted. Eventually, expectations adjust and a bust leading to a debt decline follows. Kłopocka (2017) shows that consumer confidence indexes have strong predictive power for future household borrowing.

We adopt a different approach. We argue that most of the information in popular survey measures of consumer confidence can be found in standard economic and financial indicators. This argument is supported by a sizable body of literature. Ludvigson (2004) offers a survey of the literature on the role of consumer sentiment in consumer spending dynamics. He shows that the information provided by consumer confidence predicts a relatively modest amount of additional variation in future consumer spending. More recently, Barnes and Olivei (2017) state that the role of consumer sentiment in consumption is typically small from an economic standpoint, especially when controlling for economic fundamentals. Hodula et al. (2019) show that households' expectations are tightly linked to current macroeconomic conditions.

For this purpose, we use the new Households' Macroeconomic Conditions Index (H-MCI) developed in Hodula et al. (2019). The H-MCI is a composite data-based indicator proposed in the aforementioned paper which should serve as useful approximation of the perception of macroeconomic conditions by households. It combines eleven macroeconomic variables most commonly found in the literature that jointly drive consumer confidence and expectations.

3. Empirical Framework

To explore the relationship between the H-MCI and credit dynamics at country level, we define the following dynamic panel regression for country i at time t:

$$Y_{i,t} = \alpha + \beta_1 Y_{i,t-1} + \beta_2 HMCI_{i,t-1} \cdot d_{HMCI} + \beta_3 HMCI_{i,t-1} \cdot (1 - d_{HMCI}) + \beta_4 X_{i,t-1} + v_i + \varepsilon_{i,t} \quad (1)$$

where $Y_{i,t}$ is either the year-on-year change in households' credit, households' credit gap, or households' credit-to-GDP gap. $X_{i,t}$ are supply-side control variables, v_i are fixed effects, and $\varepsilon_{i,t}$ is an error term. Households' credit gap and credit-to-GDP gap are estimated using the Hodrick-Prescott filter (for more details on the filtration, see Appendix A.1). The gaps are used in addition to the annual growth in order to focus more on the cyclical properties of household credit.

To explore potential asymmetry in the relationship, $HMCI_{i,t-1}$ is interacted with the dummy variable (d_{HMCI}), which equals 1 if the H-MCI is above zero and 0 if the H-MCI is below zero.

Introducing the dummy variable and the interaction terms allows us to explore separately periods which are favorable (above zero) or adverse (below zero) in terms of the macroeconomic and financial conditions. Given the extrapolative expectations theory discussed in section 2, favorable and adverse conditions can signal more optimistic and pessimistic expectations from the perspective of households.

The set of control variables $X_{i,t-1}$ is considered in the sensitivity analyses in order to capture some of the credit supply factors potentially influencing the evolution of credit; the set includes a proxy for bank credit risk profile ($NPL_{i,t-1}$; the ratio of banks' non-performing loans to total gross loans), a proxy for bank leverage ($capital_{i,t-1}$; the ratio of banks' equity to total assets), and a proxy for bank profitability ($ROA_{i,t-1}$; the ratio of banks' net income to total assets). Control variables are included in lagged form in order to eliminate the potential endogeneity problem.

The model is estimated using the least square dummy variable estimator.[1] To explore potential non-linearity in the relationship, the specification in eq. (1) is further estimated using the penalized quantile regression method with fixed effects as proposed by Koenker (2004).[2]

3.1 Data and Estimation Sample

Our sample covers 21 high-income OECD countries in Europe (as defined by the World Bank[3]) and 68 quarters from 2002 Q1 to 2018 Q4, giving an unbalanced panel of 1,229 observations in total.[4] Table 1 provides the final list of countries together with an indication of whether the country is categorized as advanced, is a member of the European Union, and is part of the euro area. The chosen set of countries provides a relatively homogeneous sample which still enables us to distinguish between different levels of economic development and thus determine the impact on converging economies (emerging market economies, EMEs) and developed economies (advanced economies, AEs).

Household credit and the credit-to-GDP ratio were taken from the BIS public database. Control variables were obtained from the FRED database.[5] Summary statistics by country are shown in Table A1 in Appendix A.

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[1] One of the possible identification problems in the context of dynamic panel data models with one-way fixed effects, a high number of individuals (large N), and a low number of time periods (low T) is endogeneity bias (see Nickell, 1981). Simulations by Judson and Owen (1999), however, suggest that the bias is minor in panels with more than 30 observations. Given that our panel has a relatively large number of time periods (T=68) compared to the number of individuals (N=21), the standard least square dummy variable estimator is appropriate.

[2] The estimation method is implemented using the R package *rqpd* developed by Koenker and Bache (2011). Quantile regression allows us to examine how covariates influence the location, scale, and shape of the response distribution, revealing important heterogeneity. The penalty parameter helps to shrink the fixed effects towards a common value (i.e., zero) and to reduce the variability.

[3] See, for example, World Bank (2018a, 2018b).

[4] The initial set of 26 high-income European OECD countries was reduced to 21 due to data availability.

[5] Only annual values are available; cubic spline interpolation was used to convert annual to quarterly frequency.

Table 1: Sample of Countries

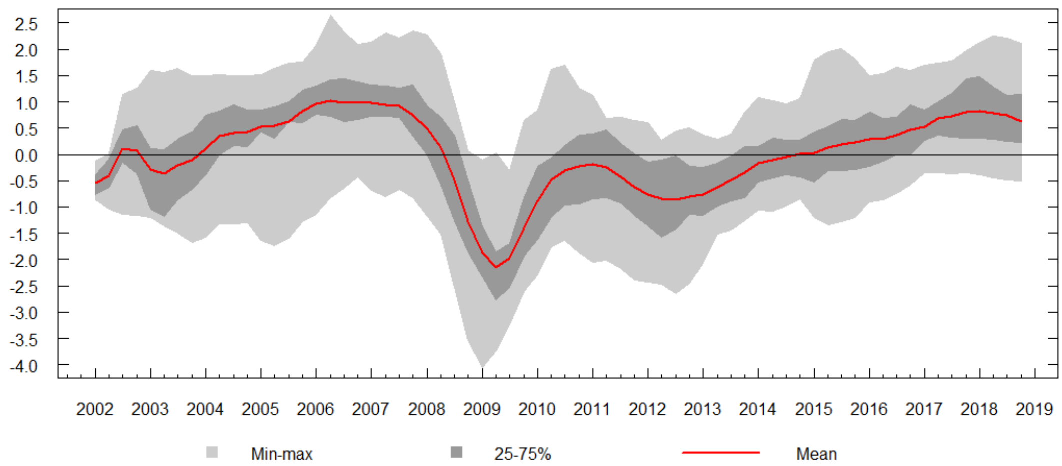
		OECD	IMF AE	EU	EA			OECD	IMF AE	EU	EA
AT	Austria	Y	Y	Y	Y	IE	Ireland	Y	Y	Y	Y
BE	Belgium	Y	Y	Y	Y	IT	Italy	Y	Y	Y	Y
CZ	Czechia	Y	2009	2004	N	LV	Latvia	2016	2014	2004	2014
DE	Germany	Y	Y	Y	Y	NL	Netherlands	Y	Y	Y	Y
DK	Denmark	Y	Y	Y	N	PL	Poland	Y	N	2004	N
EE	Estonia	2010	2011	2004	2011	PT	Portugal	Y	Y	Y	Y
ES	Spain	Y	Y	Y	Y	SE	Sweden	Y	Y	Y	N
FI	Finland	Y	Y	Y	Y	SK	Slovakia	Y	2009	2004	2009
FR	France	Y	Y	Y	Y	SL	Slovenia	2010	2007	2004	2007
GR	Greece	Y	Y	Y	Y	UK	United Kingdom	Y	Y	Y	Y
HU	Hungary	N	N	2004	N						

Note: AE – advanced economy as categorized by the IMF. Y/N indicates that the country does/does not belong to that category for the whole sample period (2002 Q1–2018 Q4); a specific year indicates the year of entry.

3.2 Households' Macroeconomic Conditions Index

We construct the H-MCI at quarterly frequency between 2002 and 2018 for all 21 countries in our sample. The list of the variables used to compute the H-MCI is shown in Table A2 in the Appendix; the methodology is described in Hodula et al. (2019). Figure 1 shows the H-MCI for our panel of countries. As is apparent, it captures the concurrent macroeconomic development well. In the period in question, the sample of countries went through a full business cycle. The mean value of the H-MCI across countries is strongly correlated with the mean value of the consumer confidence index (CCI) ($\rho = 0.80$) published and maintained by the OECD as one of its leading indicators.[6] The H-MCI thus describes fairly well the overly good macroeconomic conditions prior to the GFC and the bad times in its aftermath. The index gains momentum at the end of the sample, suggesting the onset of a new business cycle.

Figure 1: The H-MCI for Selected Countries

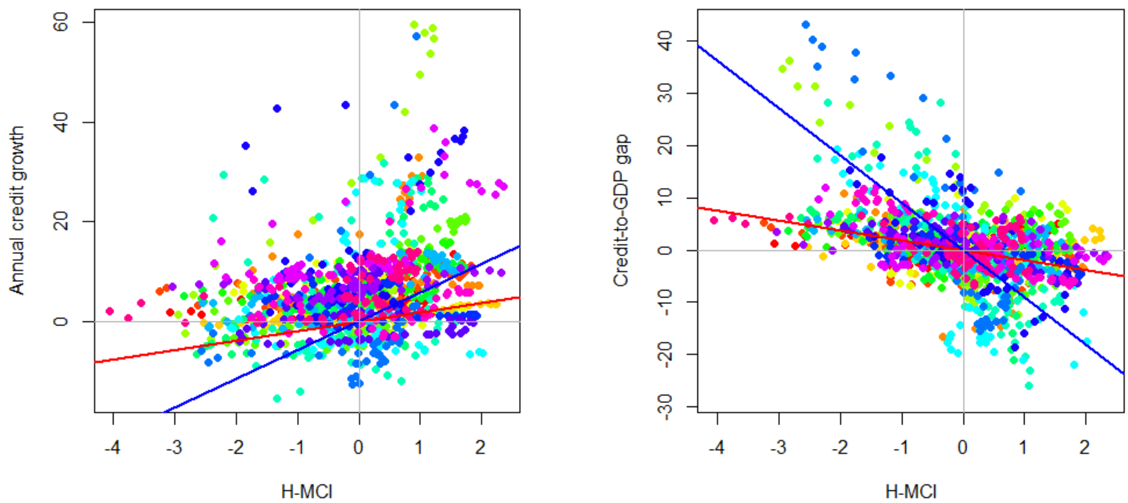


Note: The index is standardized using its long-run mean and standard deviation; the vertical axis shows the standard deviations. For more details on the construction of the H-MCI, see Hodula et al. (2019).

[6] The CCI is calculated as a simple average of answers to questions regarding respondents' past and future (expected) financial situation, expected economic situation, and unemployment expectations. It is thus constructed as forward-looking, since the questions dealing with expectations over the next 12 months are strongly favored (three to one).

Empirical studies suggest that macroeconomic indicators (GDP, household spending on consumption), labor market indicators (household income, employment), and growth in asset prices are among the key determinants of growth in loans to households (Mendoza and Terrones, 2012; Elekdag and Wu, 2013). These variables form the H-MCI, so it is not surprising that there is a positive correlation with annual household credit growth (Figure 2, left panel). The positive labor market situation, rising household incomes, and low interest rates are jointly reflected in households' willingness to take on debt. This relationship seems to be stronger for emerging market economies (blue line) than advanced economies (red line), which supports the basic convergence story. However, the relationship turns out to be negative for households' credit-to-GDP gap (right panel). As such, the behavior of households' annual credit growth can be considered procyclical, while the behavior of households' credit-to-GDP gap can be considered countercyclical. This may point to potential asymmetries and non-linearities in the relationship between households' credit and macroeconomic conditions and may have important policy implications. In the next section, we test whether the correlation survives increasingly demanding statistical tests and whether we can associate periods of overly good/bad macroeconomic conditions with credit booms/busts.

Figure 2: Relationship Between the H-MCI and Household Credit Variables



Note: The horizontal axis is in standard deviations and the vertical axis in percent. The red line refers to advanced economies and the blue line to emerging market economies.

4. Households' Macroeconomic Conditions and Credit Dynamics: An Empirical Investigation

The behavior of households' annual credit growth and credit gap can be considered procyclical, while the behavior of households' credit-to-GDP gap can be considered rather countercyclical.

The estimation results of eq. (1) are summarized in Table 2. They show that there is a positive, statistically significant relationship between a higher H-MCI and higher annual credit growth, confirming that improving macroeconomic and financial conditions encourage households to become more indebted. This relationship is stronger for emerging market economies than for advanced economies, which is consistent with the notion that the rapid credit expansion in these countries is the outcome of convergence to values typical of advanced jurisdictions (Geršl and Seidler, 2015). In particular, a one standard deviation increase in the H-MCI[7] leads to an increase in households' annual credit growth of 0.3 pp for AEs and 1.4 pp for EMEs in the short run and of 3.2 pp for AEs and 13.8 pp for EMEs in the long run, holding other factors constant.[8] The estimated relationship is linear; it therefore also holds in the opposite direction. When we control for positive and negative values of the H-MCI (which may be thought of as good/optimistic and bad/pessimistic macroeconomic conditions), we see a more pronounced effect in bad times. This means that both an improvement and a deterioration of macroeconomic conditions have a stronger impact on credit growth in an adverse economic environment. In other words, an improvement from very bad to bad macroeconomic conditions boosts credit growth, and, symmetrically, a deterioration from bad to very bad conditions significantly dampens credit growth. The relationship between the H-MCI and credit growth in good times (H-MCI above zero) also remains positive and statistically significant, though weaker. These results give a general idea about the evolution of households' credit relative to the performance of the economy. However, they do not indicate whether credit growth is below or above its sustainable level. It is important to take into account the long-run credit trend to be able to access whether households are becoming excessively indebted – which may create risks to financial stability in the long run – or whether there is still some space left for further credit expansion until the sustainable level is reached. Therefore, we complement the analysis with two other dependent variables adjusted for trends – the household credit gap and the credit-to-GDP gap.

The relationship of the H-MCI with the household credit gap is estimated to be positive (procyclical), but that with the household credit-to-GDP gap is estimated to be negative (countercyclical). Generally, the effects are stronger for EMEs, similarly to the previous set of results. What is more interesting is the different response of the two gaps in different macroeconomic environments. Specifically, the procyclicality of the household credit gap is stronger in a good macroeconomic environment (column 6). The countercyclical behavior of the household credit-to-GDP, on the other hand, remains present only when the macroeconomic conditions are adverse (column 9). The former indicates that, with improving macroeconomic conditions, households may become excessively indebted rather more easily than becoming "under-indebted" while the economy is deteriorating. This is not surprising, as credit is generally sticky on the way down. The latter then shows that in bad times, household credit cannot keep up with the deteriorating macroeconomic and financial conditions, i.e., income variables drop faster than overall household indebtedness, while in the early recovery phase the economy recovers more quickly than household credit. In good times, the relationship is not statistically significant for AEs and even turns positive for EMEs, pointing to an interesting asymmetry. This may indicate that AEs, unlike EMEs, have reached some limits on households' indebtedness in relation to income.

[7] Taking the average H-MCI across countries, a one standard deviation increase in the H-MCI refers to, for example, the period between 2016 Q1 and 2018 Q2 and a one standard deviation decrease to, for example, the period between 2008 Q1 and 2008 Q3 (Figure 1).

[8] The long-run effect is calculated as $\beta/(1-\alpha)$, where β is the coefficient on the H-MCI and α is the autocorrelation coefficient.

Overall, the results suggest that household credit is sticky on the way down and in the early recovery phase, while it goes hand in hand with the improving economy on the way up in the later phases of the cycle. Another important property identified is the asymmetry in the relationship and the strong procyclicality of household credit in periods of favorable macroeconomic conditions; this points to the fact that in good times, households tend to become more indebted or even overindebted quite easily.

These relationships remain the same even after controlling for supply-side factors (Table B1 in Appendix B).

Table 2: Mean Regression – Effect of an Increase in the H-MCI on Credit Variables

	Dependent variable (Y_t):								
	Annual growth of household credit			Household credit gap			Household credit-to-GDP gap		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Y_{t-1}	0.909***	0.899***	0.905***	0.971***	0.985***	0.984***	0.952***	0.963***	0.943***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.009)
H-MCI_{t-1}	0.476***			0.546***			-0.056		
	(0.049)			(0.041)			(0.052)		
H-MCI_{t-1} (AE)		0.321***			0.411***			-0.093*	
		(0.051)			(0.042)			(0.053)	
H-MCI_{t-1} (EME)		1.396***			1.435***			0.334**	
		(0.120)			(0.101)			(0.138)	
H-MCI_{t-1} (AE) > 0			0.263**			0.498***			0.170
			(0.112)			(0.091)			(0.110)
H-MCI_{t-1} (AE) < 0			0.346***			0.344***			-0.358***
			(0.088)			(0.074)			(0.090)
H-MCI_{t-1} (EME) > 0			0.898***			1.506***			1.302***
			(0.227)			(0.167)			(0.202)
H-MCI_{t-1} (EME) < 0			1.733***			1.369***			-0.762***
			(0.177)			(0.160)			(0.218)
Observations	1,218	1,218	1,218	1,229	1,229	1,229	1,229	1,229	1,229
Adjusted R^2	0.954	0.957	0.957	0.964	0.967	0.967	0.944	0.944	0.946

Note: This table presents estimates based on dynamic panel data regression with country fixed effects. Standard errors are reported in parentheses. ***, **, and * denote the 1%, 5%, and 10% significance levels.

4.1 Interaction Effects with the Consumer Confidence Index (CCI)

In order to support and reinforce our previous arguments, we introduce an additional dummy variable (d_{CCI}) which equals 1 if the CCI is above zero and 0 if the CCI is below zero. We interact d_{CCI} with the existing terms in eq. (1). The specification is as follows:

$$Y_{i,t} = \alpha + \beta_1 Y_{i,t-1} + \beta_2 HMCI_{i,t-1} \cdot d_{HMCI} \cdot d_{CCI} + \beta_3 HMCI_{i,t-1} \cdot (d_{HMCI} + d_{CCI} - 2 \cdot d_{HMCI} \cdot d_{CCI}) + \beta_4 HMCI_{i,t-1} \cdot (1 - d_{HMCI}) \cdot (1 - d_{CCI}) + v_i + \varepsilon_{i,t} \quad (2)$$

As such, we explore periods in which both the H-MCI and the CCI are simultaneously either above or below zero. Periods in which we observe both indicators to be above zero represent periods of favorable macroeconomic conditions and optimistic consumer confidence. On the other hand, periods in which we observe both indicators to be below zero represent periods of adverse macroeconomic conditions and pessimistic consumer confidence. The estimation results of eq. (2) are summarized in Table 3.

Table 3: Mean Regression – Interaction Effects with the CCI Dummy Variable

	Dependent variable (Y_t):					
	Annual growth of household credit		Household credit gap		Household credit-to-GDP gap	
	(1)	(2)	(3)	(4)	(5)	(6)
Y_{t-1}	0.910***	0.904***	0.976***	0.991***	0.951***	0.952***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)
H-MCI_{t-1} (both H-MCI & CCI > 0)	0.381***		0.645***		0.309***	
	(0.103)		(0.082)		(0.097)	
H-MCI_{t-1} (H-MCI & CCI different)	-0.018		0.272**		-0.046	
	(0.154)		(0.127)		(0.151)	
H-MCI_{t-1} (both H-MCI & CCI < 0)	0.626***		0.531***		-0.355***	
	(0.079)		(0.070)		(0.086)	
H-MCI_{t-1} (AE) (both H-MCI & CCI > 0)		0.308***		0.511***		0.130
		(0.107)		(0.087)		(0.106)
H-MCI_{t-1} (AE) (H-MCI & CCI different)		-0.070		0.112		-0.204
		(0.155)		(0.127)		(0.155)
H-MCI_{t-1} (AE) (both H-MCI & CCI < 0)		0.391***		0.401***		-0.296***
		(0.085)		(0.071)		(0.087)
H-MCI_{t-1} (EME) (both H-MCI & CCI > 0)		1.023***		1.403***		1.041***
		(0.218)		(0.165)		(0.201)
H-MCI_{t-1} (EME) (H-MCI & CCI different)		0.563		2.169***		1.888***
		(0.571)		(0.460)		(0.562)
H-MCI_{t-1} (EME) (both H-MCI & CCI < 0)		1.704***		1.472***		-0.548***
		(0.172)		(0.155)		(0.212)
Observations	1,218	1,218	1,218	1,218	1,218	1,218
Adjusted R^2	0.955	0.957	0.962	0.965	0.942	0.944

Note: This table presents estimates based on dynamic panel data regression with country fixed effects. Standard errors are reported in parentheses. ***, **, and * denote the 1%, 5%, and 10% significance levels.

The positive relationship between the H-MCI and annual credit growth is pronounced when both the H-MCI and the CCI are below zero. This is especially true for EMEs. The relationship is also stronger when both indices are above zero compared to when only the H-MCI is positive (column 2). The procyclicality of the household credit gap, on the other hand, is stronger when both indices are positive, a fact which seems to be driven predominantly by advanced economies; emerging market economies show the strongest procyclicality in somewhat ambiguous periods.[9] The countercyclicality of households' credit-to-GDP gap remains strong in more adverse periods. Overall, the results with the additional interaction dummy suggest that positive consumer confidence on top of overall optimistic macroeconomic conditions may boost the credit cycle,

[9] This can be explained to a large extent by supply-side control variables (see Table B2 in Appendix B).

while negative consumer confidence in periods of overall pessimistic macroeconomic conditions may exaggerate the downturn.

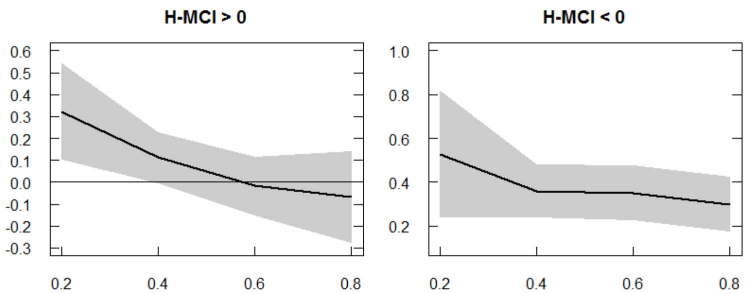
The estimates are unchanged or even more pronounced when controlling for supply-side factors (Table B2 in Appendix B).

4.2 Non-Linearity in the Relationship Between the H-MCI and Credit Dynamics

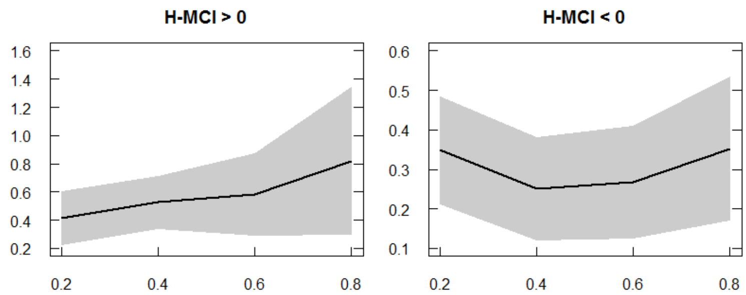
To explore the non-linearity in the relationship even further, we estimate the relationship in eq. (1) using panel data quantile regression. The results confirm our previous findings while adding some new information (see Figure 3). The procyclicality of credit growth is stronger in lower quantiles in both good and bad times (Panel A), while the procyclicality of the gap measures is stronger in higher quantiles and only in good times (Panels B and C). The latter observation is logical, because peaks in the credit cycle are closely associated with subsequent drops (Schularick and Taylor, 2009; Borio, 2012). The larger and longer is the boom, the more likely it ends up more badly (Jordà et al., 2010; Jordà et al., 2013; Dell'Ariccia et al., 2016). Further, the relationship between the H-MCI and households' credit-to-GDP gap remains countercyclical only in periods of adverse macroeconomic conditions. Together, these results have important implications. Firstly, both the credit gap and the credit-to-GDP gap continue to widen even if they are already high and quite open, creating potential for credit bubbles. Then, once the business cycle turns down and economic conditions deteriorate, the existing household indebtedness is no longer matched by sufficient income growth, i.e., income growth anticipated at the moment of loan origination. This may lead to defaults and/or extensions of repayment periods having serious consequences for the financial sector.

Figure 3: Quantile Regression – Effect of an Increase in the H-MCI on Credit Variables

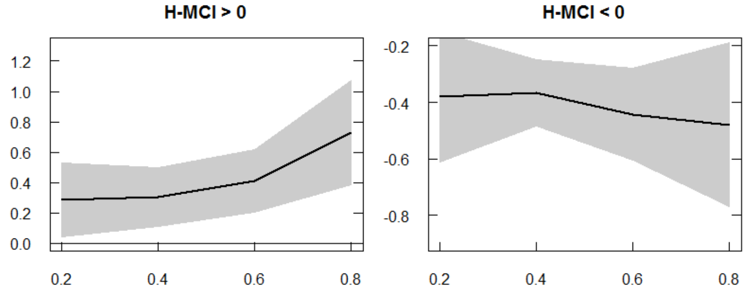
Panel A) Dependent variable – annual growth of household credit



Panel B) Dependent variable – household credit gap



Panel C) Dependent variable – household credit-to-GDP gap



Note: X-axis – quantiles, y-axis – coefficient size; 90% confidence intervals reported. The full regression results are given in Appendix B.2, Tables B3 and B4. Specifications without supply-side control variables.

5. Conclusion

We focus on the link between households' macroeconomic conditions, the confidence of households as investors and consumers, and the evolution of credit extended to households. Using a series of panel regressions on an international sample of 21 high-income European OECD countries, we provide sound empirical evidence that links households' macroeconomic conditions with the evolution of household credit. It turns out that the well-known procyclicality of credit to households is reinforced in periods of good macroeconomic conditions. This relationship is fueled by the optimistic expectations of households, which gives empirical support to the concept of extrapolative expectations. Furthermore, we report evidence pointing to the presence of non-linearities in the modeled relationship. In particular, we show that the credit of households is sticky on the way down, while it goes hand in hand with the improving economy during an economic upturn.

Using our simple framework, we cannot distinguish between rational household behavior driven solely by fundamentals and irrational household behavior driven by non-fundamental factors. It can be assumed that favorable macroeconomic conditions accompanied by optimistic consumer confidence might stimulate and shape households' expectations in such a way that they start to behave somehow irrationally, or at least their rationality is bounded. Sustained growth of household credit has contributed to strong adverse effects in a number of advanced economies several times in history, most recently during the GFC. In particular, the combination of fast income growth and low interest rates can give rise to optimistic expectations that can be gradually extrapolated to the view that good times will last "forever". Households can then be inclined to accept a much higher level of indebtedness (higher than they would be willing to take on if they were to correctly perceive a discontinuation of the positive trend in the future). This issue deserves further analysis, and it is hoped that this study will stimulate further empirical investigation in this field.

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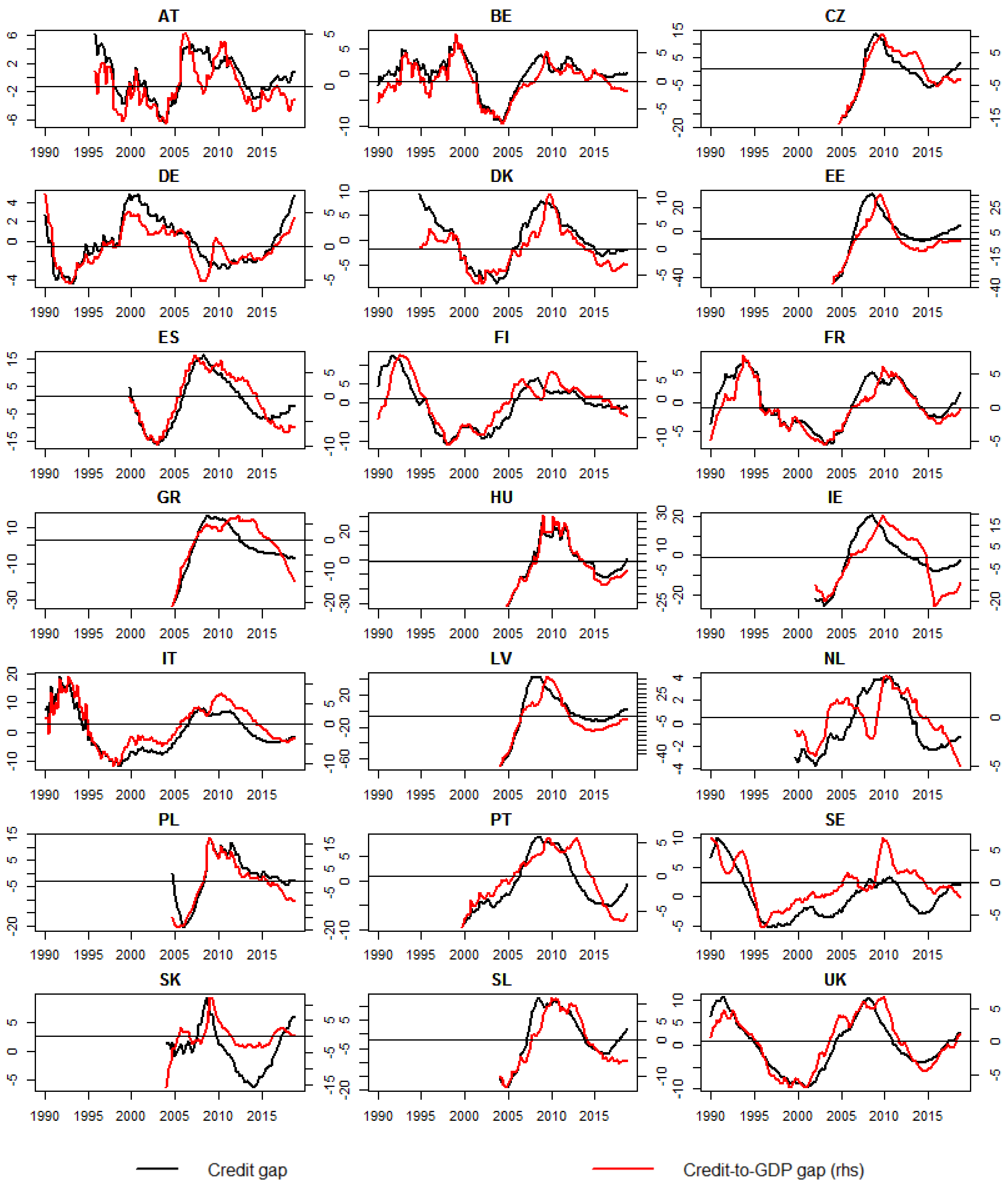
Appendix A: Data and Filtration

A.1 Hodrick–Prescott Filter

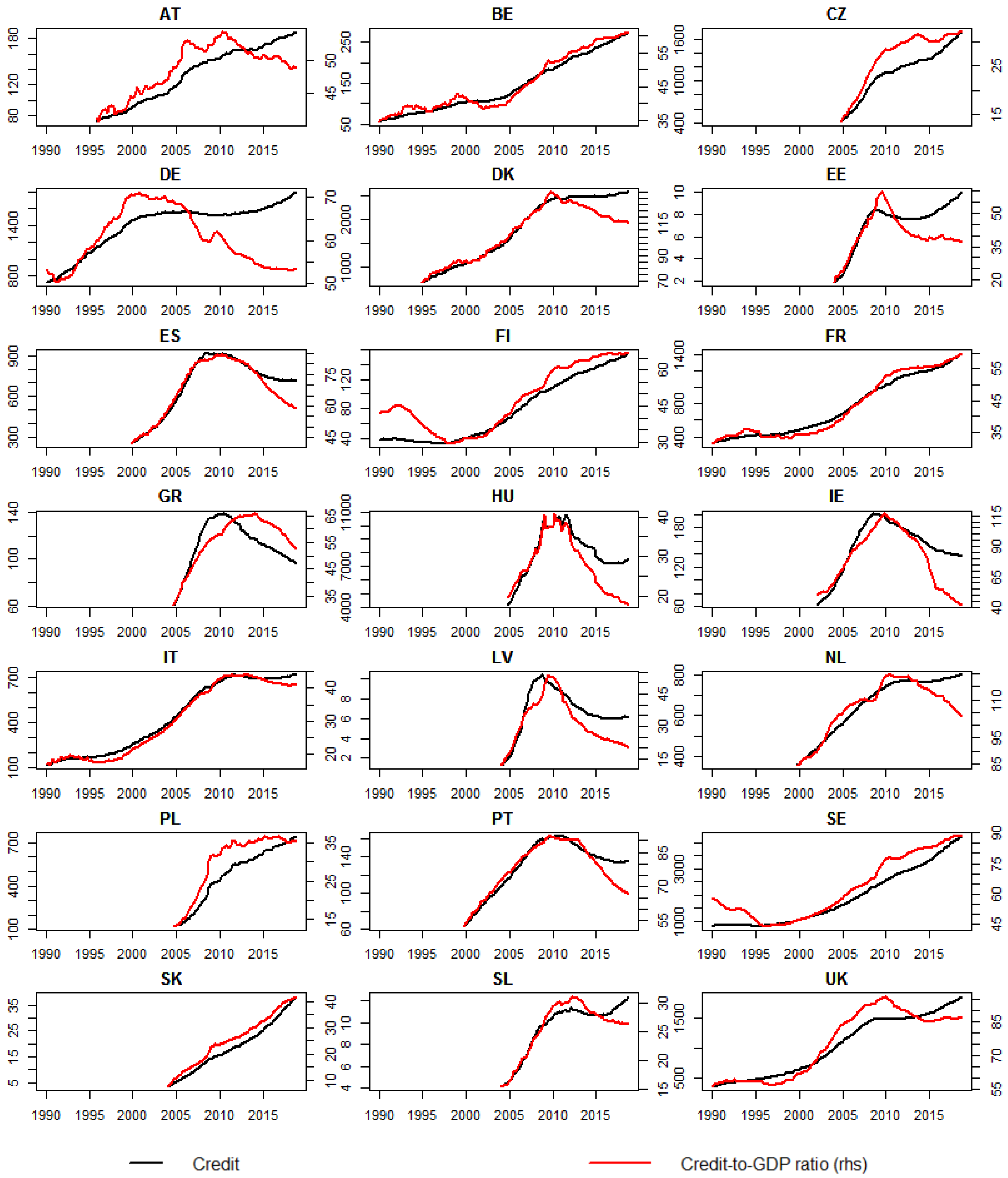
The household credit gap and credit-to-GDP gap are estimated using data from the BIS and the Hodrick-Prescott filter with λ=26,000, reflecting the fact that the credit cycle is longer than the business cycle while taking into account the length of the sample and the frequency of the data (Drehmann and Yetman, 2018). The maximum time span used is between 1990 Q1 and 2018 Q2; for some countries a shorter period is used based on data availability and quality.

Figure A1: The Household Credit Gap and Credit-to-GDP Gap for Selected Countries (%)



Note: Both gaps (the credit gap and the credit-to-GDP gap) are estimated by filtering household credit and the household credit-to-GDP ratio and then expressed as a percentage of the respective trends.

Figure A2: The Household Credit and Credit-to-GDP Ratios for Selected Countries



Note: Credit is in billions of domestic currency; credit-to-GDP ratio is in percent.

A.2 Data

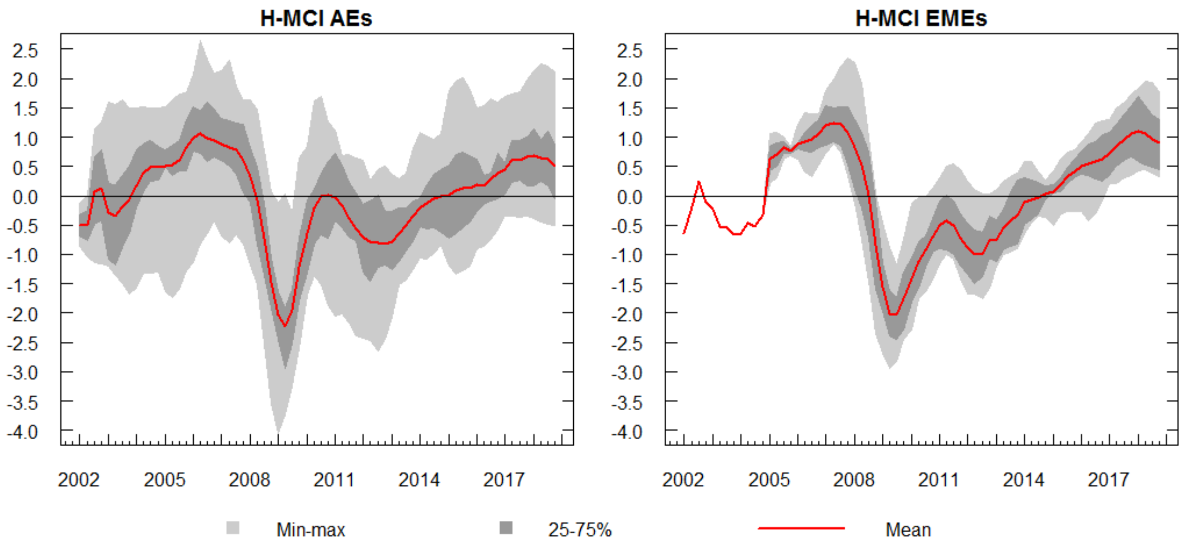
Table A1: Summary Statistics

	Annual growth of household credit (%)		Household credit gap (%)		Household credit-to-GDP gap (%)		ROA (%)		NPL (%)		Capital to assets (%)	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
AT	3.9	2.9	-0.2	2.9	0.0	2.1	0.5	0.4	2.7	0.4	6.3	1.2
BE	5.6	3.2	-0.9	3.6	-0.7	3.1	0.4	0.6	2.9	0.8	4.5	1.6
CZ	10.7	9.5	-0.6	8.0	-0.5	7.0	1.4	0.3	6.0	4.7	6.2	0.8
DE	1.0	1.3	0.3	2.3	0.2	2.5	0.1	0.2	3.6	1.0	4.7	0.7
DK	4.9	4.5	-0.9	4.9	-0.6	4.3	0.5	0.4	2.4	1.8	6.1	0.8
EE	13.2	20.4	-1.5	18.3	-1.0	16.1	1.7	2.1	1.7	1.6	10.2	1.6
ES	5.8	9.8	-1.3	9.1	-0.6	5.6	0.5	0.6	3.8	2.9	6.9	0.8
FI	7.6	4.1	-0.8	4.4	-0.5	4.5	0.6	0.3	0.5	0.1	6.4	1.7
FR	5.9	3.0	-0.7	3.7	-0.5	3.2	0.3	0.2	3.9	0.7	5.3	0.9
GR	3.5	11.6	-0.7	11.8	-0.4	7.2	-0.7	2.3	17.2	12.3	7.4	1.8
HU	4.6	13.3	-1.0	14.4	-1.1	14.4	0.9	1.2	7.3	5.4	8.4	0.6
IE	5.3	12.4	-1.6	12.5	-2.1	12.8	-0.1	1.6	9.0	8.9	7.2	3.4
IT	5.8	5.5	-0.5	5.2	-0.1	4.0	0.2	0.8	10.1	4.6	6.1	1.0
LV	14.4	34.6	-2.7	27.2	-2.2	21.8	0.7	1.6	5.1	4.9	9.0	1.2
NL	4.3	3.7	-0.2	2.5	-0.1	2.4	0.6	0.7	2.3	0.6	4.5	0.9
PL	14.5	13.3	-1.3	8.7	-0.9	9.6	0.8	1.3	8.9	6.1	8.3	0.6
PT	3.9	6.5	-0.5	5.2	-0.3	3.8	-0.1	1.3	5.5	4.0	6.5	0.9
SE	7.7	2.0	-0.4	2.2	0.0	2.3	0.7	0.2	1.0	0.4	5.0	0.6
SK	17.6	12.1	0.4	4.0	-0.2	4.4	1.0	0.3	5.4	2.8	9.6	1.8
SL	8.0	9.4	-0.8	9.3	-0.5	7.4	-	-	-	-	-	-
UK	5.8	4.6	-0.3	5.3	0.2	3.9	0.5	0.5	2.3	1.1	6.4	1.5
AE	5.2	6.3	-0.6	6.1	-0.5	5.2	0.4	1.0	4.7	5.9	6.3	2.1
EME	17.6	23.3	-1.4	18.9	-0.9	16.2	1.0	1.5	6.3	5.7	8.3	1.5
Total	**7.0**	**11.6**	**-0.7**	**9.4**	**-0.5**	**8.0**	**0.5**	**1.2**	**5.1**	**5.9**	**6.8**	**2.1**

Table A2: Data Used to Estimate the H-MCI

Block	ID	Description	Source	Units
I	1	Gross domestic product, current prices, annual levels, seasonally adjusted	OECD	National currency, millions
	2	Gross disposable income, households and non-profit institutions serving households, current prices, quarterly levels, seasonally adjusted*	OECD	National currency, millions
	3	Gross savings, households and non-profit institutions serving households, current prices, quarterly levels, seasonally adjusted*	OECD	National currency, millions
II	4	Compensation of employees, households, current prices, quarterly levels, seasonally adjusted	OECD	National currency, millions
	5	Average registered number of employees, seasonally adjusted	OECD	Thousand persons
III	6	Bank interest rates on consumer loans, households, outstanding amounts	ECB, national statistical office or central bank	% pa
	7	Bank lending rate on loans for house purchase, households, outstanding amounts	ECB, national statistical office or central bank	% pa
IV	8	Residential property prices, nominal, broadest available (i.e., all types of dwelling)	BIS, ECB	2010=100
	9	Share price index	BIS	2010=100
V	10	BIS effective exchange rates, nominal, broad index, quarterly averages	BIS	2010=100
	11	Terms of trade, calculated as ratio of export prices to import prices, exports/imports of goods and services, seasonally adjusted	OECD	2010=100

Figure A3: The H-MCI for Advanced Economies and Emerging Market Economies



Note: The index is standardized using its long-run mean and standard deviation; the vertical axis shows the standard deviations. For more details on the H-MCI, see Hodula et al. (2019).

Appendix B: Additional Regression Results

B.1 Mean Regression Analysis

Table B1: Mean Regression – Effect of an Increase in the H-MCI on Credit Variables (2)

	Dependent variable (Yt):								
	Annual growth of household credit			Household credit gap			Household credit-to-GDP gap		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Y_{t-1}	0.891***	0.882***	0.888***	0.966***	0.979***	0.977***	0.957***	0.962***	0.947***
	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)	(0.009)
H-MCI_{t-1}	0.515***			0.462***			-0.107*		
	(0.061)			(0.047)			(0.055)		
H-MCI_{t-1} (AE)		0.369***			0.345***			-0.129**	
		(0.062)			(0.048)			(0.057)	
H-MCI_{t-1} (EME)		1.451***			1.253***			0.075	
		(0.138)			(0.110)			(0.143)	
H-MCI_{t-1} (AE) > 0			0.274**			0.300***			-0.021
			(0.136)			(0.106)			(0.125)
H-MCI_{t-1} (AE) < 0			0.435***			0.348***			-0.298***
			(0.100)			(0.079)			(0.093)
H-MCI_{t-1} (EME) > 0			1.072***			1.516***			1.025***
			(0.258)			(0.176)			(0.209)
H-MCI_{t-1} (EME) < 0			1.720***			0.991***			-0.984***
			(0.209)			(0.174)			(0.222)
ROA_{t-1}	0.081	-0.022	-0.053	0.257***	0.167***	0.179***	0.170***	0.158***	0.200***
	(0.062)	(0.062)	(0.064)	(0.048)	(0.048)	(0.048)	(0.057)	(0.058)	(0.057)
NPL_{t-1}	-0.029*	-0.045***	-0.041**	-0.085***	-0.090***	-0.092***	-0.102***	-0.105***	-0.101***
	(0.016)	(0.016)	(0.017)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
CA_{t-1}	-0.014	0.024	0.015	-0.116***	-0.056	-0.039	-0.154***	-0.137***	-0.099**
	(0.048)	(0.047)	(0.048)	(0.037)	(0.037)	(0.037)	(0.044)	(0.045)	(0.045)
Observations	1,097	1,097	1,097	1,108	1,108	1,108	1,108	1,108	1,108
Adjusted R^2	0.959	0.961	0.961	0.968	0.970	0.970	0.948	0.948	0.950

Note: This table presents estimates based on dynamic panel data regression with country fixed effects. Standard errors are reported in parentheses. ***, **, and * denote the 1%, 5%, and 10% significance levels.

Table B2: Mean Regression – Interaction Effects with the CCI Dummy Variable (2)

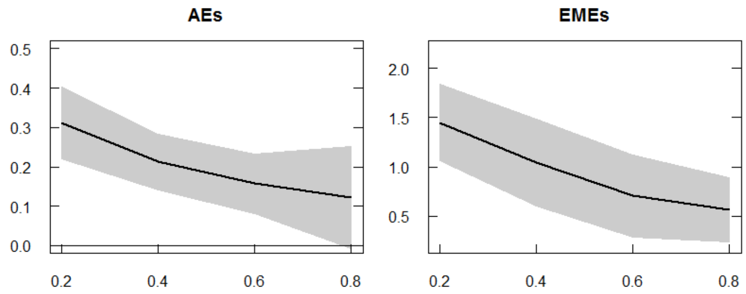
	Dependent variable (Y_t):					
	Annual growth of household credit		Household credit gap		Household credit-to-GDP gap	
	(1)	(2)	(3)	(4)	(5)	(6)
Y_{t-1}	0.892^{***}	0.887^{***}	0.966^{***}	0.979^{***}	0.955^{***}	0.951^{***}
	(0.008)	(0.008)	(0.006)	(0.006)	(0.009)	(0.010)
$H\text{-}MCI_{t-1}$	0.446^{***}		0.568^{***}		0.193^{*}	
(both H-MCI & CCI > 0)	(0.123)		(0.092)		(0.107)	
$H\text{-}MCI_{t-1}$	0.051		0.206		-0.082	
(H-MCI & CCI different)	(0.166)		(0.131)		(0.152)	
$H\text{-}MCI_{t-1}$	0.660^{***}		0.440^{***}		-0.344^{***}	
(both H-MCI & CCI < 0)	(0.093)		(0.076)		(0.089)	
$H\text{-}MCI_{t-1}$ (AE)		0.331^{**}		0.345^{***}		-0.040
(both H-MCI & CCI > 0)		(0.132)		(0.103)		(0.121)
$H\text{-}MCI_{t-1}$ (AE)		0.004		0.116		-0.180
(H-MCI & CCI different)		(0.168)		(0.132)		(0.157)
$H\text{-}MCI_{t-1}$ (AE)		0.480^{***}		0.373^{***}		-0.269^{***}
(both H-MCI & CCI < 0)		(0.096)		(0.076)		(0.090)
$H\text{-}MCI_{t-1}$ (EME)		1.196^{***}		1.486^{***}		0.838^{***}
(both H-MCI & CCI > 0)		(0.249)		(0.176)		(0.211)
$H\text{-}MCI_{t-1}$ (EME)		0.700		1.322^{***}		1.029^{*}
(H-MCI & CCI different)		(0.601)		(0.471)		(0.557)
$H\text{-}MCI_{t-1}$ (EME)		1.694^{***}		1.075^{***}		-0.829^{***}
(both H-MCI & CCI < 0)		(0.200)		(0.170)		(0.217)
ROA_{t-1}	0.059	-0.050	0.260^{***}	0.172^{***}	0.192^{***}	0.192^{***}
	(0.063)	(0.064)	(0.048)	(0.048)	(0.058)	(0.058)
NPL_{t-1}	-0.029^{*}	-0.041^{**}	-0.082^{***}	-0.089^{***}	-0.094^{***}	-0.100^{***}
	(0.016)	(0.017)	(0.012)	(0.012)	(0.014)	(0.014)
CA_{t-1}	-0.026	0.007	-0.121^{***}	-0.044	-0.149^{***}	-0.102^{**}
	(0.048)	(0.048)	(0.037)	(0.038)	(0.044)	(0.047)
Observations	1,097	1,097	1,097	1,097	1,097	1,097
Adjusted R^2	0.959	0.961	0.965	0.967	0.946	0.947

Note: This table presents estimates based on dynamic panel data regression with country fixed effects. Standard errors are reported in parentheses. ***, **, and * denote the 1%, 5%, and 10% significance levels.

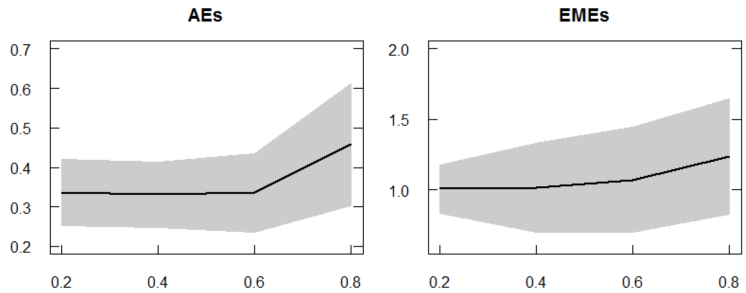
B.2 Quantile Regression Analysis

Figure B1: Quantile Regression – Effect of an Increase in the H-MCI on Credit Variables (2)

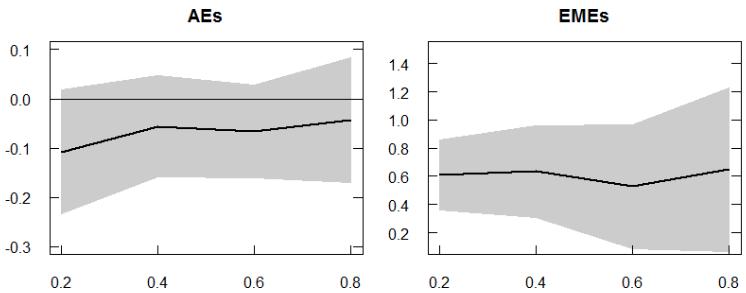
Panel A) Dependent variable – annual growth of household credit



Panel B) Dependent variable – household credit gap



Panel C) Dependent variable – household credit-to-GDP gap



Note: X-axis – quantiles, y-axis – coefficient size; 90% confidence intervals reported. The full regression results are given in Appendix B.2, Tables B3 and B4. Specifications without supply-side control variables.

Table B3: Quantile Regression – Effect of an Increase in the H-MCI on Household Credit Variables (1)

	Dependent variable (Y_t):											
	Annual growth of household credit				Household credit gap				Household credit-to-GDP gap			
	Q 0.20	Q 0.40	Q 0.60	Q 0.80	Q 0.20	Q 0.40	Q 0.60	Q 0.80	Q 0.20	Q 0.40	Q 0.60	Q 0.80
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	-0.245**	0.115**	0.371***	0.729***	-0.573***	-0.239***	0.117*	0.61***	-1.001***	-0.497***	-0.187***	0.281***
	(0.095)	(0.047)	(0.061)	(0.118)	(0.116)	(0.064)	(0.066)	(0.12)	(0.17)	(0.074)	(0.071)	(0.09)
Y_{t-1}	0.893***	0.943***	0.965***	0.993***	0.945***	0.961***	0.969***	0.981***	0.917***	0.939***	0.941***	0.953***
	(0.018)	(0.012)	(0.01)	(0.016)	(0.012)	(0.008)	(0.008)	(0.014)	(0.017)	(0.01)	(0.008)	(0.012)
$H\text{-}MCI_{t-1} > 0$	0.323**	0.114	-0.017	-0.068	0.417***	0.526***	0.583***	0.821***	0.288*	0.305**	0.41***	0.732***
	(0.133)	(0.07)	(0.081)	(0.125)	(0.115)	(0.112)	(0.175)	(0.317)	(0.147)	(0.118)	(0.125)	(0.208)
$H\text{-}MCI_{t-1} < 0$	0.529***	0.361***	0.352***	0.3***	0.349***	0.251***	0.268***	0.353***	-0.381***	-0.366***	-0.443***	-0.48***
	(0.174)	(0.073)	(0.075)	(0.074)	(0.083)	(0.078)	(0.086)	(0.11)	(0.14)	(0.072)	(0.099)	(0.176)

Note: This table presents estimates based on dynamic panel data quantile regression with country fixed effects. Standard errors are reported in parentheses. ***, **, and * denote the 1%, 5%, and 10% significance levels.

Table B4: Quantile Regression – Effect of an Increase in the H-MCI on Household Credit Variables (2)

	Dependent variable (Y_t):											
	Annual growth of household credit				Household credit gap				Household credit-to-GDP gap			
	Q 0.20	Q 0.40	Q 0.60	Q 0.80	Q 0.20	Q 0.40	Q 0.60	Q 0.80	Q 0.20	Q 0.40	Q 0.60	Q 0.80
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	-0.317***	0.035	0.27***	0.589***	-0.516***	-0.133***	0.226***	0.802***	-0.717***	-0.249***	0.152***	0.787***
	(0.107)	(0.061)	(0.057)	(0.122)	(0.061)	(0.025)	(0.032)	(0.106)	(0.069)	(0.021)	(0.034)	(0.109)
Y_{t-1}	0.881***	0.93***	0.957***	0.989***	0.962***	0.976***	0.981***	0.997***	0.938***	0.953***	0.959***	0.975***
	(0.017)	(0.015)	(0.012)	(0.015)	(0.008)	(0.008)	(0.01)	(0.013)	(0.011)	(0.006)	(0.008)	(0.012)
H-MCI_{t-1} (AE)	0.311***	0.213***	0.158***	0.122	0.336***	0.332***	0.336***	0.458***	-0.107	-0.056	-0.066	-0.044
	(0.056)	(0.043)	(0.046)	(0.079)	(0.051)	(0.05)	(0.06)	(0.094)	(0.076)	(0.063)	(0.057)	(0.077)
H-MCI_{t-1} (EME)	1.451***	1.041***	0.704***	0.563***	1.007***	1.018***	1.072***	1.239***	0.609***	0.636***	0.528**	0.647*
	(0.236)	(0.269)	(0.253)	(0.2)	(0.104)	(0.193)	(0.227)	(0.249)	(0.15)	(0.198)	(0.266)	(0.354)

Note: This table presents estimates based on dynamic panel data quantile regression with country fixed effects. Standard errors are reported in parentheses. ***, **, and * denote the 1%, 5%, and 10% significance levels.

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