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The Response of Household Debt to Consumer Confidence Shocks in Germany, Italy and France

Sanja Celcer[1]
Doctoral Student in Economics Science at the Faculty of Economics and Business, University of Maribor, Slovenia
Email: sanja.celcer@gmail.com

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Abstract

The purpose of this paper is to study whether and how consumer confidence affects household debt dynamics in three largest economies in the euro area, Germany, Italy and France, by employing vector autoregressive model and impulse response analysis on the data for the period 1999Q1–2024Q1. The results suggest substantial heterogeneity of household debt responses to consumer confidence shocks. Specifically, improved consumer confidence leads to a fall in household debt in Germany, initially after the shock. In contrast, household debt in Italy increases with a delay of three quarters after a positive shock to consumer confidence. In France, unlike in Germany and Italy, the response of household debt to an unexpected increase in consumer confidence is not significant. Additionally, the impulse responses of macroeconomic fundamentals to the shocks in consumer confidence were analyzed and compared across the sampled countries. Finally, the robustness of the results was tested using an alternative measure of household debt.

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1. Introduction

Household debt plays a critical role in macroeconomic dynamics, influencing both consumption patterns and financial stability. As households borrow to finance consumption, investments, and housing, debt can stimulate economic growth in the short term. However, excessive household debt can increase vulnerability to economic shocks, leading to financial instability, reduced consumption, and slower recovery during downturns (see e.g. Mian et al., 2015; Lombardi et al., 2017; Zabai, 2017; Alter et al. 2018). Consequently, understanding the determinants of household debt is essential for policymakers aiming to balance economic growth with economic and financial stability in the long term.

The ability to consume is influenced by household (disposable) income and accumulated wealth, whereas the willingness to spend is driven by consumer confidence, which is shaped by households' subjective perception and expectations of both national economic and personal financial conditions (Katona, 1968). People's sentiments play a crucial role in shaping their economic behaviour and decisions. Although intangible, sentiments are connected to expectations, judgments, emotions, and beliefs, and are typically measured through indexes designed to capture their fluctuations (Daskalopolou, 2023). In economic analysis, confidence has been shown to influence market outcomes, with evidence of reverse causality as well (ibidem). Therefore, the predictive power of confidence and the indexes used to track its variations is a central concern in evaluating economic conditions and assessing an economy's growth potential (ibidem).

In contrast to the empirically documented effects of changes in sentiment (i.e., consumer confidence) on economic growth and business cycles (see e.g., Matsusaka and Sbordone, 1995; Leduc and Sill, 2013; Beaudry and Portier, 2014; van Aarle and Moons, 2017), consumption (see e.g., Throop, 1992; Carroll et al., 1994), savings (see e.g., Kłopocka, 2017; Vanlaer et al., 2020) and investment (e.g., Khan et al., 2020) decisions, the role of consumer confidence as a potential determinant of fluctuations in household debt is largely overlooked, rarely acknowledged and empirically tested.

This paper aims to examine the effects of consumer confidence shocks on household debt in Germany, Italy and France, by applying the vector autoregressive model and impulse response analysis and accounting for macroeconomic fundamentals. Only a limited number of studies (e.g., Brown et al., 2005; Brown et al., 2008; Kłopocka, 2017; Angelico, 2019 and Gric et al., 2022) examine the impact of consumer confidence on household loan growth or household debt. These studies, however, did not examine the consumer confidence index as measured by DG ECFIN, used the indicator for household debt defined as a ratio of total household financial liabilities to gross disposable income adjusted for the pension entitlements, or did not apply the impulse response analysis to examine the impacts of shocks on household debt. This paper aims to fill this gap for the three studied countries.

2. Literature Review

The relevant group of studies related to the identified gap in the literature primarily includes research from Brown et al. (2005), Brown et al. (2008), Kłopocka (2017), Angelico (2019) and Gric et al. (2022). Brown et al. (2005) used a random effects TOBIT model to examine the determinants of household debt in the UK, with a focus on the impact of households' financial expectations (obtained from British Household Panel Survey (BHPS) data in 1995 and 2000). Their findings show that optimistic expectations about future financial conditions have a statistically significant and positive effect on both, household debt level and growth, at both the individual and aggregate levels. Brown et al. (2008) investigate the factors influencing the growth of household mortgage debt in the UK. The study focuses on the impact of households' financial expectations regarding their future financial situation on mortgage debt levels. Using data from the BHPS, the authors find that optimistic financial expectations significantly contributed to the increase in mortgage debt levels between 1993 and 2001.

Kłopocka (2017) examined (among others) whether the consumer confidence index significantly explains the saving and borrowing tendencies of Polish households from 2002Q1 to 2014Q3. Data on consumer confidence were obtained from the European Commission's survey on business and consumer trends, and analyzed using multiple linear regressions. One of the key findings is that both the current consumer confidence index and the index of consumer confidence for the next 12 months have a significant impact on predicting future movements in the gross savings rate and gross borrowing rate of Polish households (Kłopocka, 2017). Using a vector autoregressive (VAR) model, Angelico (2019) analyzed U.S. data from 1968Q4 to 2016Q1 and found that household survey data (SPF) on expected economic growth is a strong predictor of future household debt trends. The results align with Friedman's permanent income hypothesis, suggesting that optimistic expectations lead to higher borrowing, while pessimistic expectations encourage saving. According to this hypothesis, economic agents increase borrowing if they expect a rise in their permanent income, and conversely, they increase saving if they anticipate a decline in permanent income. Similarly, Gric et al. (2022), in the first part of their study, used a fixed-effects panel regression model to examine the relationship between a modified consumer confidence index

(based on data from the European Commission's survey on business and consumer trends) and the growth of newly approved consumer loans for a sample of 15 selected European Union countries from January 2003 to March 2019. Their findings indicate that the modified consumer confidence index has a positive and statistically significant impact on the growth rate of newly approved consumer loans.

The other literature on determinants of household debt does not investigate the role of expectations and/or consumer confidence. The list of those studies includes e.g. Alfaro et al. (2012), Meng et al. (2013), Wildauer (2016), Malinen (2016), Moore and Stockhammer (2018), Coletta et al. (2019), Enache (2022) and Jumpanoi and Wanasilp (2022). The empirical literature on the determinants of household debt either focuses on single-country or a panel of countries or explores a wide range of factors affecting debt, including microeconomic, macroeconomic, financial, demographics as well as institutional constraints. These determinants can generally be categorized into supply-side and demand-side factors (see e.g., Meng et al., 2013; Coletta et al., 2019). For example, Alfaro et al. (2012) analyze household debt default in Chile, applying probit models and 2007 Survey of Household Finances data. Observing personal and financial characteristics of households, they find that income and education level of consumers are key robust predictors of default risk for mortgage debt, while, income and age for consumer debt.

Meng et al. (2013) explore the determinants of Australian household debt (i.e., stock of household nominal accumulated liabilities) for the period 1988Q2 to 2011Q2 by employing a co-integrated vector auto-regression (CVAR) model. Key finding of the research is that housing prices is the most significant and positive determinant of Australian household debt, followed by GDP and population. Higher GDP can lead to increased household debt because it may imply higher household income and may decrease the share of credit constrained households. Consequently, as households loan demand (willingness and ability to borrow) and the supply (willingness to lend) of loans increase, household debt may rise. Official interest rates (i.e., Australian central bank base rate), unemployment rate, the number of new dwellings approvals and inflation were found to have a negative impact on household debt, with official interest rates being the most influential factor. Meng et al., clarifies (2013) that interest rate increases elevate borrowing costs, discouraging household borrowing or diminishing their borrowing propensity. Households with variable-rate debt, like most Australian housing loans, face higher repayment costs when interest rates rise. Meng et al. (2013) further explains that higher interest rates indirectly reduce investment, which slows the economy and can lead to lower household income, higher unemployment, and reduced borrowing. When new debt falls below scheduled repayments, household debt levels decline. Debelle (2004) suggests that low inflation contributes to rising household debt by reducing its financial constraints (lower inflation leads to lower interest rates, reducing the income needed for scheduled payments) and encouraging lending (lower inflation causes the principal to erode more slowly).

Wildauer (2016) investigates two popular explanations of US households´ debt increase for the period from 1989 to 2001– the expenditure cascades hypothesis (i.e., the influence of increasing property prices) and the Minskyian households' hypothesis (i.e., the impact of rising income inequality). Utilizing the Survey of Consumer Finances (SCF) data, the author finds that households engage in status-driven, debt-financed expenditures only when they have access to collateral, supporting the expenditure cascades hypothesis. Rising real estate prices are shown to significantly increase household indebtedness through home purchases. Additionally, the study confirms the Minskyian household hypothesis, where rising real estate prices drive borrowing through equity extraction and demand for larger mortgages, especially among first-time buyers.

Malinen (2016) examined the relationship between income inequality and bank credit (measured as household loans to real GDP) using a panel co-integration framework, first-difference estimations, and Granger causality tests for 8 OECD countries for the period 1960 – 2008. The study found that income inequality contributed to the increase of bank credit in developed economies after World War II. Furthermore, results show a negative relationship between short-term interest rates (proxy for central bank policy rate) and household debt, although the robustness of this finding is uncertain, as it is statistically significant in only two out of three relevant specifications. Specifically, for the period from 1980 to 2008 results indicate significantly negative relationship between the share of household loans to real GDP and real GDP per capita growth and short-term interest rates, respectively.

Moore and Stockhammer (2018) empirically tests seven competing hypotheses[2] on the macroeconomic determinants of household debt (as a percentage of GDP) across 13 OECD countries from 1993 to 2011. Error correction models were employed to analyze both long-term and short-term effects. Real residential house prices were found to be the most robust determinant of household debt in both the long-run and short-run, with cycle-dependent asymmetric effects on debt accumulation (i.e., boom periods significantly influence the findings).

[2] Those hypotheses are the house price hypothesis, the financial asset hypothesis, the expenditure cascades hypothesis, the falling wages hypothesis, the welfare retrenchment hypothesis, the age structure hypothesis and the low-interest rate hypothesis respectively together in a comprehensive framework (see Moore and Stockhammer (2018) for an in-depth discussion).

Additionally, Granger causality tests indicate causality from real residential house prices to household debt, emphasizing the importance of including house prices in studies on household debt determinants and support the house price hypothesis. Age structure has some long-term significance, while financial assets and falling wages show weak short-term effects.

Coletta et al. (2019) examined both demand and supply side macroeconomic factors as determinants of household debt (measured as households' financial debt to disposable income) in 33 OECD countries (27 European Union member states, Australia, Canada, Japan, New Zealand, South Korea, and the United States) for the period 1995- 2016 by applying the multivariate panel approach. Authors found that supply-side factors are more robust in influencing household debt than demand-side factors. Specifically, the study identifies a significantly positive relationship between household debt and wealth and house prices, respectively. The authors, among other findings, discovered that unemployment rate is also positive and statistically significant factor of household debt, indicating that households tend to increase their debt during cyclical downturns. Furthermore, the quality of bankruptcy laws plays a crucial role in influencing household debt levels, with creditors more willing to extend loans when they are better protected.

Enache (2022) analyses household debt (represented as the loans granted by credit institutions to individuals) response to economic shocks in Romania from 2011Q1 to 2021Q4 using a Structural Vector Autoregressive model. The author finds that loans respond positively to the shocks to average net wage, negatively and insignificantly to the shocks to the interest rates on loans and positively to its own shocks.

Jumpanoi and Wanasilp (2022) explore the determinants of Thai household debt (measured as loans or outstanding loans from financial institutions) from a macro-level perspective for the period 2007Q1 – 2022Q1 by employing the ARDL (i.e., autoregressive distributed lag) modelling approach to determine the long-run relationship among the variables. The study found that in the long run unemployment rates negatively, while lending interest rates and the working-age population positively impact Thai household debt.

3. Data & Methodology

3.1. Data

This research uses data for the period 1999Q1 – 20241Q1 for three largest members of the euro area: Germany (GER), Italy (ITA) and France (FRA). Table 1 provides a detailed description of the variables included in the three econometric VAR models, data sources, and data transformations.

Table 1. Description of variables

Variable id	Description
cci_{ct}	Seasonally adjusted consumer confidence indicator[3]. Average quarterly level is computed from monthly data and expressed in percentage. The source of consumer confidence data is European Commission´s (2024a) Business and Consumer Surveys. The time series was not transformed.
$logdebt_{ct}$	Quarterly household's gross debt to income ratio in country c at time t, calculated as the ratio (in percent) of the stock of loans liabilities (i.e., A.F4) to household's gross disposable income (B.6G, flows) with the latter being adjusted for the net change in pension entitlements in pension fund reserves (i.e., D.8, flows) as the four quarter cumulative annual moving sums (see equation 1)[4] (see Kozina and Tartamella, 2019; ESA 2010, 2013, ECB, 2024). Data on the stock of loan

[3]The Consumer Confidence Indicator is calculated as an arithmetic average of the (seasonally adjusted) balances (in percentage points) of responses to questions about the past and expected financial situation of households, the expected general economic situation in the next 12 months, and major purchases intentions over the next 12 months (European Commission, 2024b). Thus, an increase in consumer confidence reflects an increase in the fraction of consumer with positive perceptions or beliefs about their own financial situation over the past and next 12 months, general economic situation in a country in the next 12 month and major purchases intentions in the next 12 month, relative to the fraction of consumer with a negative perceptions or beliefs (European Commission, 2024b).

[4]The following equation was used to compute the household's gross debt to income ratio (see e.g., Kozina and Tartamella, 2019):

$$Gross\ households\ debt\ to\ income\ ratio = \left(\frac{A.F4_{c,t}}{sum\ \Sigma\ (B.6G_{c,t\ to\ t-4} + D.8\ Net_{c,t\ to\ t-4})}\right) * 100.$$

Formula for the household indebtedness indicator (i.e., gross household debt to income ratio) follows the internationally recognized methodology of the System of National Accounts (ESA 2010, 2013; SNA 2008, 2009) and is endorsed by reputable institutions like Eurostat (2023a) and the ECB (2024).

	liabilities were obtained from Eurostat (2024a) and are available only in a non-seasonally adjusted format. Therefore, we applied the Tramo/Seats method of the JDemetra+ software to seasonally adjust this data for all three countries included in the sample over the observed time period. Data on households' gross disposable income and net adjustment for the change in pension fund reserves is seasonally adjusted and obtained from Eurostat (2024b). The natural logarithm of the $debt_{ct}$ was computed.
$loggdpindex_{ct}$	Seasonally and calendar adjusted quarterly real (chain linked volumes) index (2015 = 100) of gross domestic product (GDP_{ct}), obtained from Eurostat (2024d). Transformation of quarterly real GDP_{ct} index into the natural logarithms was conducted.
$loghicpindex_{ct}$	Quarterly Harmonised Index of Consumer Prices (2015 = 100), obtained from Eurostat (2024f). Quarterly data of $HICP_{ct}$ was computed from monthly data by geometric mean method, because indices used for computation of inflation involve multiplicative rather than additive characteristics (see Eurostat, 2024e for additional methodological details). Eurostat (2024f) provided data in a non-seasonally adjusted format, hence seasonal adjustment of $HICP_{ct}$ was performed using the Tramo/Seats method in JDemetra+ software (see Eurostat 2024c and ECB (2000) for further methodological information). The $HICP_{ct}$ was transformed into the natural logarithms.
$shadowrate_t$	Shadow rate of the European Central Bank, reflecting the stance of the monetary policy in the euro area (expressed in %), obtained from Krippner (2024)[5]. Quarterly averages were computed from daily data.
$loghpir_{ct}$	Quarterly real house price index (2015 = 100). The data series are seasonally adjusted and obtained from the OECD (2024). Quarterly real house price index ($hpir_{ct}$) series was transformed into the natural logarithms.

Source: Author's own construction.

Figure 1 illustrates the quarterly evolution of consumer confidence in Germany, Italy and France from 1999Q1 to 2024Q1 and highlights its key declines during major economic events. The dynamics of consumer confidence were relatively synchronized across countries until 2010Q2. Notably, from 2001Q2 to 2005Q2, German households were generally more pessimistic than those in France and Italy. The first significant drop in consumer confidence across all three observed countries aligns with the Global Financial Crisis (2007-2009), which caused widespread financial instability. From 2010Q3 a divergence in the dynamics of consumer confidence emerged between Germany on one side, and France and Italy on the other. German households exhibited higher consumer confidence (i.e., were notably less pessimistic) compared to those in France and Italy. A second decline occurred during the Euro area's double-dip recession (2012-2013), driven by sovereign debt crises and austerity measures. The most recent sharp decline corresponds with the onset of the COVID-19 pandemic in 2020Q2 with a subsequent drop in 2022, as global uncertainty and economic disruption intensified.

[5]For more details regarding how the shadow rate can be used to indicate the monetary policy stance during the zero lower bound period, see Krippner (2015).

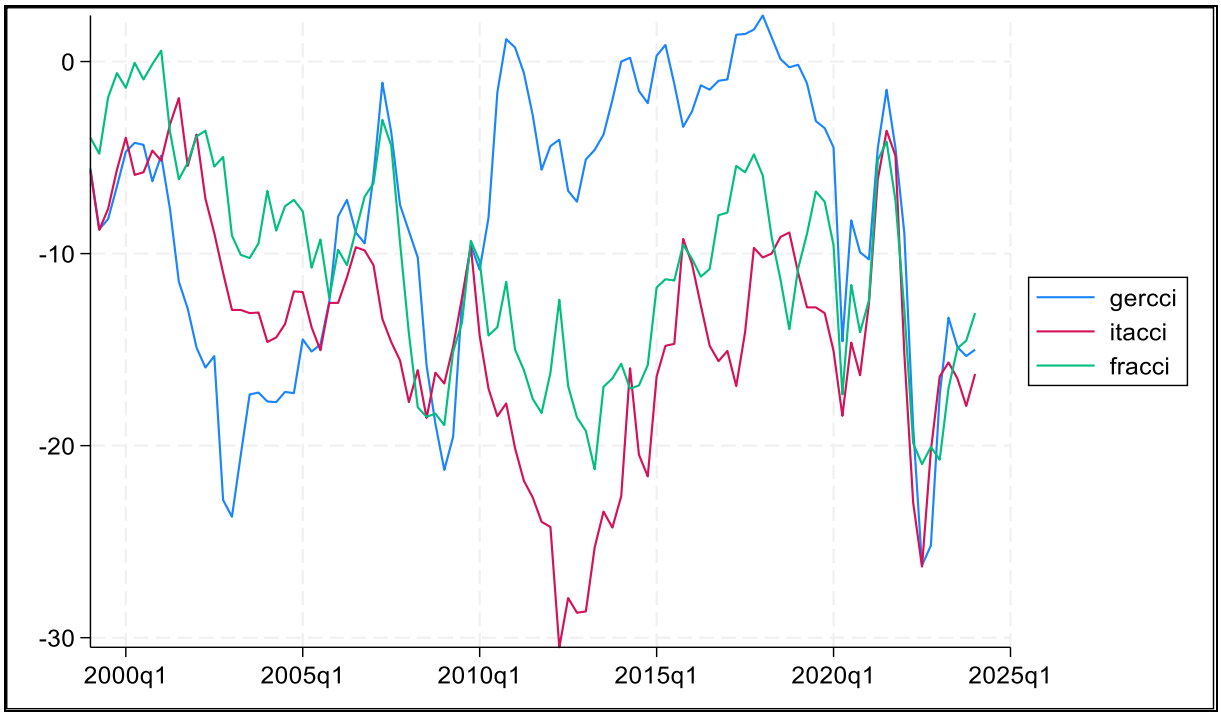

Figure 1. The Evolutions of Consumer Confidence in Germany, Italy and France during the Analyzed Period

Source: Author´s own construction, based on data from European Commission (2024a).

Figure 2 display the quarterly evolution of household debt in Germany, Italy and France from 1999Q1 to 2024Q1. At the beginning of the period, household debt in Germany reached 105% of their disposable income which was significantly higher than in Italy and France, where household debt levels stood at 30% and 55% of their disposable income, respectively. Following this period, household debt gradually increased in both Italy and France. In Italy, it rose until the end of 2014Q2, while in France it exceeded Germany's household debt level in 2013Q2 and continued to rise until the end of 2022Q3. On the contrary it declined in Germany until 2019Q1. At the end of the observed period, the highest household debt to disposable income is observed in France (94 %), followed by Germany (81 %) and Italy (57 %). In Germany, household debt stood below its long-term average of 91%, while in Italy and France, it remained above their long-term averages of 55% and 80%, respectively.

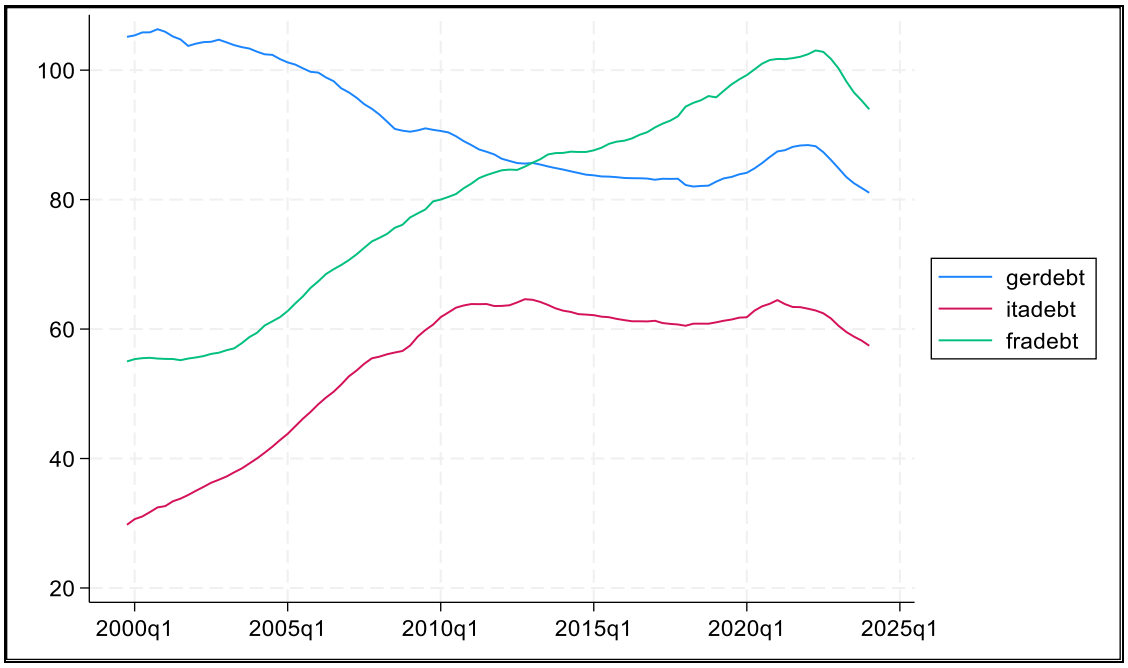

Figure 2. The Evolutions of Household Debt in Germany, Italy and France During the Analyzed Period

Source: Author´s own construction, based on data from the Eurostat (2024a, 2024b).

3.2 Methodology

A vector autoregressive (VAR) model is applied to analyze the dynamic responses of household debt to consumer confidence shocks in Germany, Italy and France. VAR models, first proposed by Chris Sims in the 1970s and 1980s, are commonly applied in econometrics and various disciplines to study the dynamic interactions between multiple time series. Each time series variable is represented as a linear function of its own lagged values, the lagged values of all other variables in the system, and a serially uncorrelated error term. All variables in the VAR models are treated as endogenous, meaning that each variable in the system can influence and be influenced by the others (Stock and Watson, 2001). Lütkepohl and Krätzig (2004) describe the standard formulation of the VAR model of order $p(VAR_{(p)})$ as follows:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \quad (2)$$

where $y_t = (y_{1t}, \ldots, y_{kt})'$, is a $k \times 1$ vector of the endogenous variables at time t, $A_1, \ldots, A_p$ are $k \times k$ are regression coefficient matrices for each lag p, capturing the relationships between the variables and $u_t = (u_{1t}, \ldots, u_{kt})'$ is an unobservable error term or independent white noise or innovation process, distributed with a zero mean and time-invariant positive definite covariance matrix $\mathrm{E}(u_t u_t') = \Sigma_u$. Our sample includes three countries therefore we estimate three countries VAR models. The selection of the endogenous variables in the models is based on the approach outlined by Leduc and Sill (2013).

As noted by Sims, Stock, and Watson (1990) and Hamilton (1994), the VAR empirical literature typically models variables in (log) levels rather than growth rates. Therefore, variables, $debt_{ct}$, $gdpindex_{ct}$, $hicpindex_{ct}$, $hpir_{ct}$ enter the models in log levels, while cci_{ct} and $shadowrate_t$ in levels. We estimated the same specified baseline model separately for each country. The vector of the endogenous variables consists of $y_t = (cci_{ct}, loggdpindex_{ct}, loghicpindex_{ct}, shadoweate_t, loghpir_{ct}, logdebt_{ct})'$.

The literature is not entirely unified on the necessity of variable stationary. Some authors, such as Sims (1980), argue that differencing or removing non-stationary can obscure important relationships between variables, as the essence of VAR analysis lies in understanding the dynamic interactions rather than just focusing on parameter estimation. Sims, Stock, and Watson (1990) emphasize that this approach is especially pertinent in applied research, where it is common to combine stationary and non-stationary series. In such contexts, the primary focus is often on impulse response functions, variance decompositions, or forecast accuracy, rather than on strictly adhering to stationary conditions. Enders (1995) supports this view, asserting that even when non-stationary variables are included, the parameter estimates of the VAR model remain consistent (Enders, 1995, p. 301). Canova and Ciccarelli (2009) highlight that traditional approaches to non-stationary, such as differencing, might lead to a loss of information, especially when analysing cross-country relationships. Therefore, according to Sims, Stock, and Watson (1990), results of our three VAR models are consistent even if the variables entering the model are a combination of stationary and non-stationary time series. The results generated in Stata are not displayed here to conserve space but are available upon request.

Before estimating the VAR model, it is necessary to select the optimal lag length. The lag structure in VAR captures the time-delayed effects that variables have on each other and determines how many past values of the variables will be included in the model (see e.g., Sims, Stock, and Watson, 1990; Lütkepohl and Krätzig, 2004). The selection of the lag length was based on the Akaike Information Criterion (i.e., AIC). Drawing on the results from the AIC information criteria, we opted to use two lags for Germany and four lags for Italy and France. After estimating the three country's VAR models, we further assessed the presence of autocorrelation in the residuals of each country's VAR model using the Lagrange-multiplier test, as proposed by Johansen (1995). The null hypothesis is that there is no autocorrelation at the selected lag. The results suggest than there is no autocorrelations at two and four lags in our three country VAR models (i.e., for each country VAR models: p-value at two lags for Germany and four lags for Italy and France is bigger than 0.05, thus we cannot reject the null hypothesis). The results of the lag length selection and the tests for autocorrelation of residuals at the selected lag are not displayed here to conserve space but are presented in the Appendix: part 1 (Figures 9, 10 and 11) and part 3 (Figures 15, 16, and 17). All computations were performed in Stata.

For computing and analyzing the (orthogonal) impulse responses functions, the identification of shocks is implemented by a Cholesky decomposition of the covariance matrix of residuals. Therefore, the ordering of the variables in the models is of great importance (Lütkepohl et al., 2005). Since the covariance matrix of residuals is lower triangular matrix, this implies that a shock to the first variable has an immediate impact on all other variables in the model, while a shock to the second variable does not immediately affect the first variable. By

employing the Cholesky decomposition, we impose an ordering of the variables' endogeneity, requiring that variables be ranked by based on economic theory (Lütkepohl and Krätzig, 2004; Lütkepohl et al., 2005). As we noted above, we follow Leduc and Sill (2013) and ordered consumer confidence first, followed by two macroeconomic variables including economic activity and consumer price index. Next in the order is monetary policy stance represented as shadow rate, followed by house price index (suggested by Moore and Stockhammer, 2018). Households' indebtedness indicator is positioned last, under the assumption that it is contemporaneously influenced by all other variables within the empirical model. Following Leduc and Sill (2013), we positioned consumer confidence ahead of other macroeconomic variables in the model because it is measured for the upcoming 12-month period, as outlined by the European Commission (2024b).

4. Empirical analysis

4.1. Results and Discussion

Figure 3 shows the orthogonalized impulse responses to a positive one standard deviation shock to consumer confidence for Germany. Results show that consumer confidence has a short-term negative effect on household debt and positive effects on GDP (lasting about 6 quarters). A significant negative effect on household debt lasts for about 7 quarters after the shock, with its maximum impact of approximately 0.3 percent, occurring one quarter earlier.

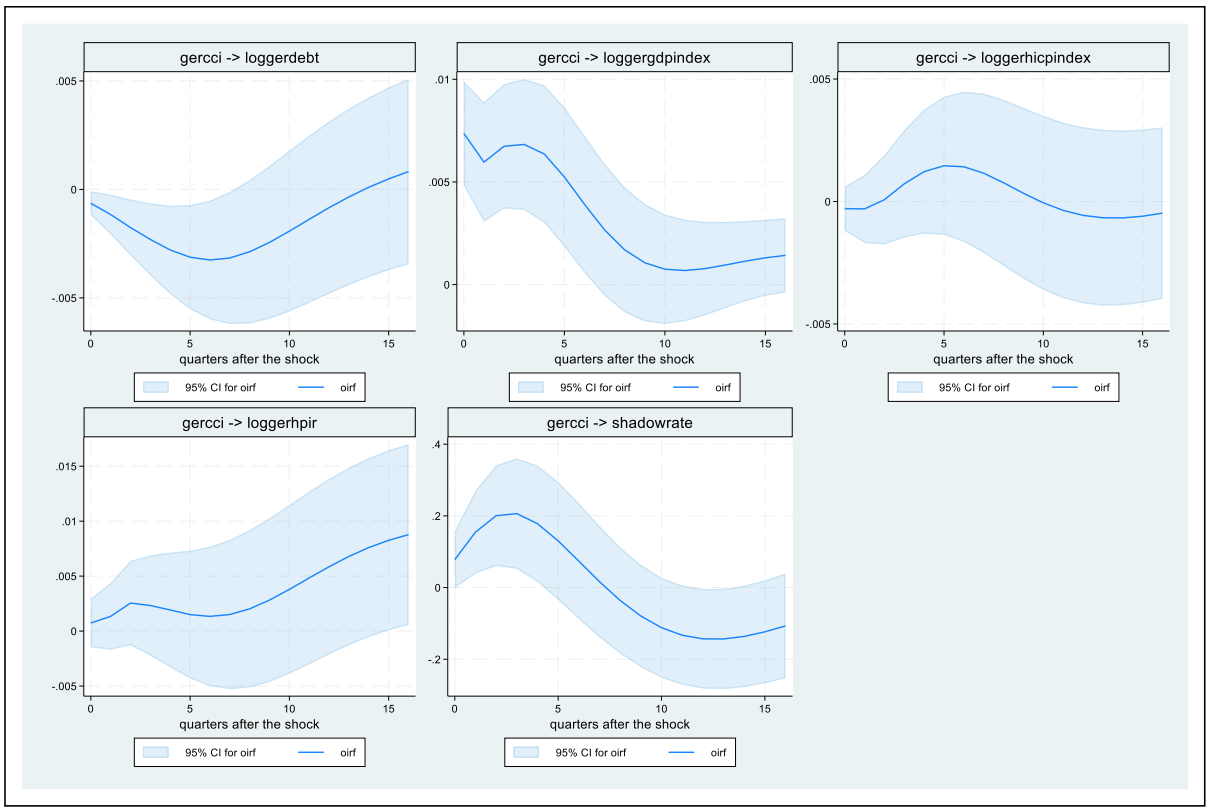

Figure 3. The effects of a consumer confidence shock in Germany

Source: Authors own calculations.

A shock has the greatest impact on GDP immediately after it occur (reaching approximately 0.7 percent), but after about four quarters (i.e., one year) the positive effect starts to diminish. The ECB's monetary policy shadow rate responds significantly positively to the confidence shock from the first to the fourth quarter after the initial shock and negatively from the twelfth to the thirteenth quarter after the shock occurs. The shock reaches its maximum positive impact of approximately 0.2 percent three quarters after the initial shock, while its maximum negative impact occurs after the thirteenth quarter and reached approximately 0.1 percent. House prices significantly increase three and a half years after the shock occurs, with the peak impact of approximately 0.9 percent estimated in the final quarter.

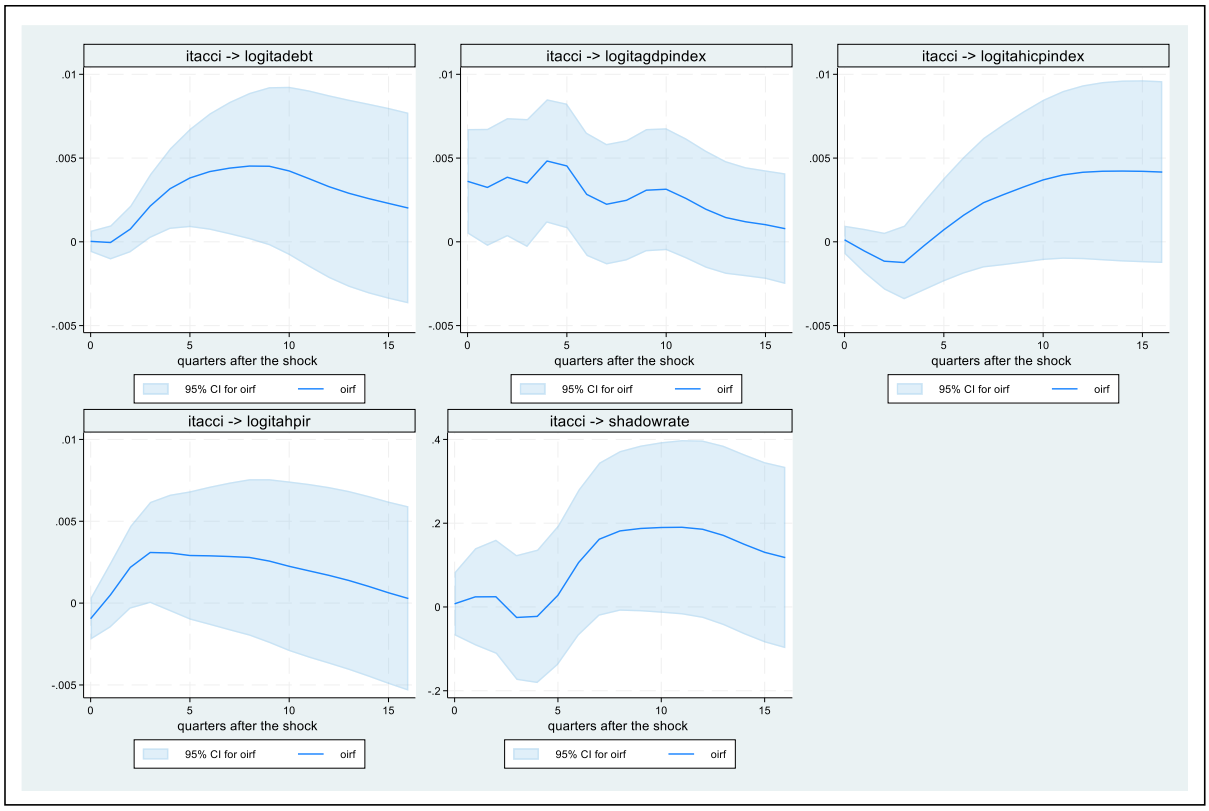

Figure 4. The effects of a consumer confidence shock in Italy

Source: Authors own calculations.

Figure 4 show the orthogonalized impulse responses to a positive one standard deviation shock to consumer confidence in Italy. The response of household debt to consumer confidence shock in Italy is significantly positive, short run and more delayed than in Germany. Specifically, the consumer confidence shock leads to a significant increase in household debt over the course of three to eight quarters, with the impact peaking in the eight quarter, where household debt increases by approximately 0.5 percent. The effects on GDP are significant initially after the shock occur. Additionally, the response of GDP to the shock becomes significant again after two quarters and once more between the fourth and fifth quarters following the shock, with the strongest response occurring in the fourth quarter, where GDP increases by 0.5 percent. The impulse response of house prices to a shock is significantly positive only in the third quarter, leading to increase in house prices of approximately 0.3 percent. The response of both the HICP and the ECB's monetary policy stance do not appear to be significantly sensitive to consumer confidence shocks.

In contrast to the results for Germany and Italy, the response of household debt to a shock to consumer confidence in France remains unaffected (i.e., is not statistically significant) over the entire observed time horizon (16 quarters) from the shock. The effect of consumer confidence shock on GDP is significantly positive only around two quarters after the shock and then again in the fourth and six quarter following the shock. The highest impact of the shock on GDP is estimated to occur immediately after the shock, with GDP increasing by 0.7 percent. Additionally, the response of the HICP to the consumer confidence shock becomes significantly positive between the sixth and seventh quarters following the shock, with the highest impact observed in the seventh quarter, resulting in a 0.3 percent increase. Meanwhile, the consumer confidence shock leads to an about one year-long increases in house prices immediately following the shock, with its maximum impact of approximately 0.5 percent occurring in the third quarter. The response of the ECB's monetary policy shadow rate to the confidence shock remains significantly positive, persisting for about eight quarters after the initial shock. The shock reaches its highest impact on ECB's monetary policy stance, of approximately 0.3 percent, six quarters following the shock.

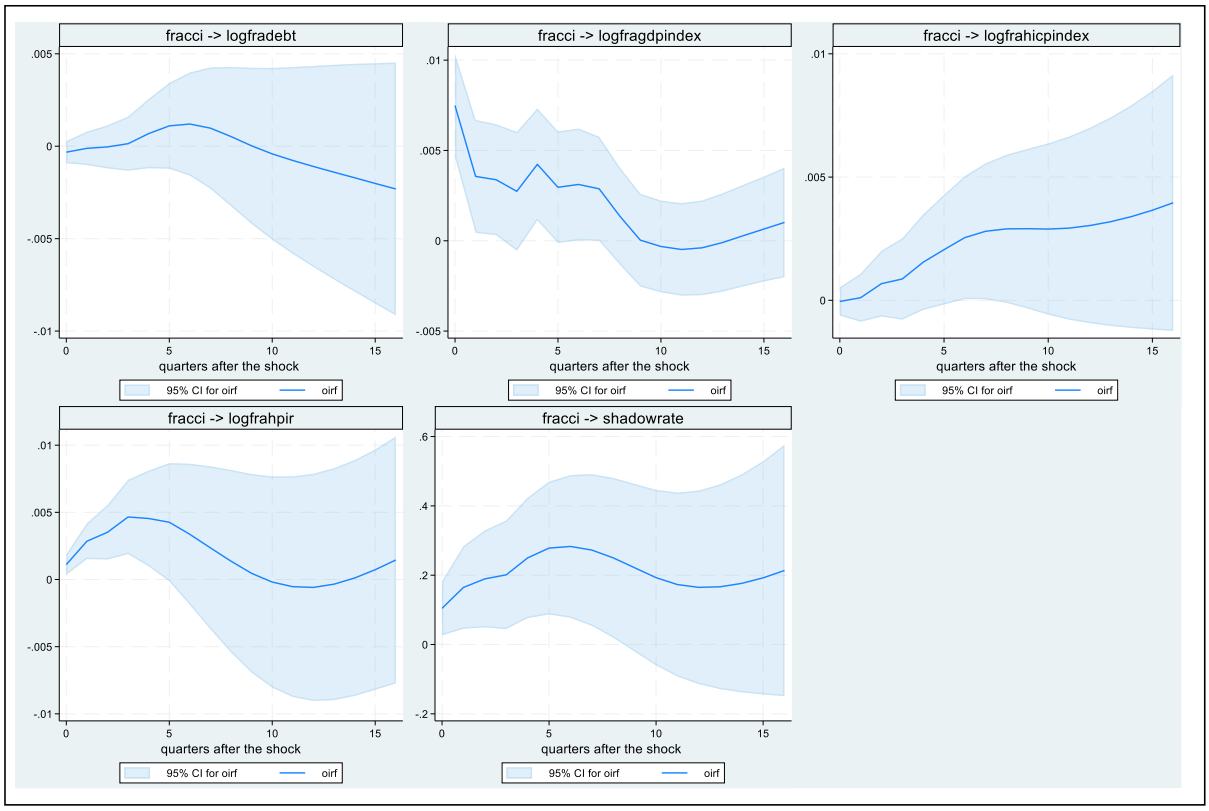

Figure 5. The effects of a consumer confidence shock in France

Source: Authors own calculations.

Our results for Italy suggest than an increased consumer confidence can contribute to the increased household debt, which coincides whit the findings from Brown et al. (2005), Brown et al. (2008), Kłopocka (2017), Angelica (2018) and Gric et al. (2022). When consumer confidence in Italy is high, households tend to be more optimistic about their future financial and overall economic conditions. This optimism leads them to feel more secure about their (future) financial situation, making them more likely to take on loans for consumption, housing, or investment.

These findings are also supportive by permanent income hypothesis (Friedman, 1957) and life-cycle hypothesis (Modigliani & Brumberg, 1954). According to the permanent income hypothesis, individuals make consumption and borrowing decisions based on anticipated lifetime income rather than current income (Friedman, 1957). High consumer confidence signals optimism about future earnings, encouraging households to borrow more, while declining confidence leads to increased saving and reduced borrowing (Friedman, 1957). The life-cycle hypothesis suggests that individuals plan their consumption and savings over their lifetime to maintain a stable standard of living. Increased consumer confidence may lead households to borrow during periods of lower income, expecting future income growth to cover debt repayment, thus contributing to rising household debt levels (Modigliani & Brumberg, 1954). Additionally, asymmetric information and moral hazard in credit markets could further illustrate how shifts in consumer sentiment influence borrowing behaviour, supported by credit market theories as suggest by Stiglitz and Weiss (1981). When consumer confidence is high, lenders often perceive borrowers as less risky, resulting in increased credit availability and lower borrowing costs. This supply-side effect, coupled with greater demand for loans from optimistic households (consumers), can drive household debt growth (ibidem).

In contrast, the response of household debt to a positive shock in consumer confidence is negative in Germany, indicating that higher consumer confidence leads to a reduction in household debt. This implies a more cautious approach to debt accumulation during periods of increased consumer optimism, as households in Germany may choose to save more or reduce debt, driven by a sense of financial security regarding their future prospects. Börsch-Supan and Lusardi (2003) explore the saving and borrowing behaviour of households across different countries, including Germany, showing that German households tend to be more cautious about debt, especially during periods of economic optimism. Additionally, a positive shock to consumer confidence in Germany boosts the GDP, while the ECB's monetary policy shadow rate tightens. As Lane (2023) notes, policy tightening can elevate credit risk and lead to tighter credit conditions for households, which in turn may contribute to reduced debt or borrowing. In France, however, the response of household debt to a positive shock in consumer

confidence is left unaffected, while it leads to a rise in GDP and house prices. Consumer confidence may affect other areas of the France economy, potentially through increased consumption or investment, but without leading people to take on more debt. In France, more confident households might spend more or invest in real estate, pushing up demand for housing (which raises house prices) and boosting economic activity (GDP) (see e.g., Khan et al., 2019, who find similar results for US), even though they are not borrowing to finance these activities.

4.2. Robustness tests

The robustness of the results reported in Figures 6, 7 and 8 are evaluated using an alternative measure of household debt, that is the ratio of total household financial liabilities from loans (i.e., A.F4) to gross domestic product (i.e., household debt to GDP ratio) as the four quarter cumulative annual moving sums. Household debt to GDP ratio entering the models in log levels (i.e., $logdebtgdp_{ct}$). The analysis of the robustness check results primarily focused on the response of household debt to GDP ratios to consumer confidence shocks in Germany, Italy, and France, respectively. The AIC information criteria suggested using four lags for all three country's VAR models: Germany, Italy, and France (Figures 12, 13, and 14 in the Appendix, part 2). The results of the Lagrange-multiplier test (as proposed by Johansen, 1995) indicate no autocorrelation at four lags for each country's VAR model. Specifically, the p-values at four lags for Germany, Italy, and France exceed 0.05, thereby supporting the null hypothesis that there is no autocorrelation at the selected lag (Figures 18, 19, and 20 in the Appendix, part 3).

The results of these robustness checks support the findings in our baseline VAR model for households in Germany (see Figure 3 and Figure 6). The response of household debt to a positive shock in consumer confidence for Germany is of the same direction (i.e., negative) and persistence of the shock (i.e., from the initial impact to the seventh quarter), as reported in Figure 3. Additionally, Figure 6 illustrates that GDP initially increases after the shock in consumer confidences, while the ECB's monetary policy shadow rate tightens. The effect of shock of consumer confidence on GDP lasting about 6 quarters, while on ECB's monetary policy stance lasts about 5 quarters after the shock occur. On the other hand, between the eleventh and fourteenth quarters after the shock, the ECB's monetary policy response turns negative. House prices increase three years after the shock occurs, which is half a year earlier than the results illustrated in Figure 3. Furthermore, the responses of HICP to the shock on consumer confidence (unlike in baseline VAR model reported in Figure 3) become significant in the second quarter and again between the fifth and sixth quarters following the shock. In general, the results from Figure 6 indicate that the robustness check findings for Germany are similar to those reported in Figure 3.

For Italy, the impulse responses of household debt and house prices to a positive shock in consumer confidence become statistically insignificant (see Figures 4 and 7). In addition, the response of the HICP and the ECB's shadow rate remained non-significant, while the significant response of GDP remained in the same direction and similar persistence, which is consistent with the results presented in Figure 4. Italy is the most sensitive to alternative measure of household debt. Following a shock in consumer confidence, France's household debt initially increases significantly, with this effect persisting for approximately three quarters (see Figure 8). Overall, the responses of GDP, house prices and ECB's monetary policy shadow rate to a shock in consumer confidence in France are similar to the results presented in Figure 5 in terms of direction, magnitude, and persistence (see Figure 8). The persistence of the ECB's monetary policy response mirrors that observed in the baseline VAR model, lasting approximately eight quarters following the initial shock. The effect of a consumer confidence shock on HICP demonstrates the same direction, a similar magnitude, and greater persistence, lasting from the fourth to the eighth quarter, compared to the baseline VAR model, where persistence is observed from the sixth to the seventh quarter (see Figures 5 and 8).

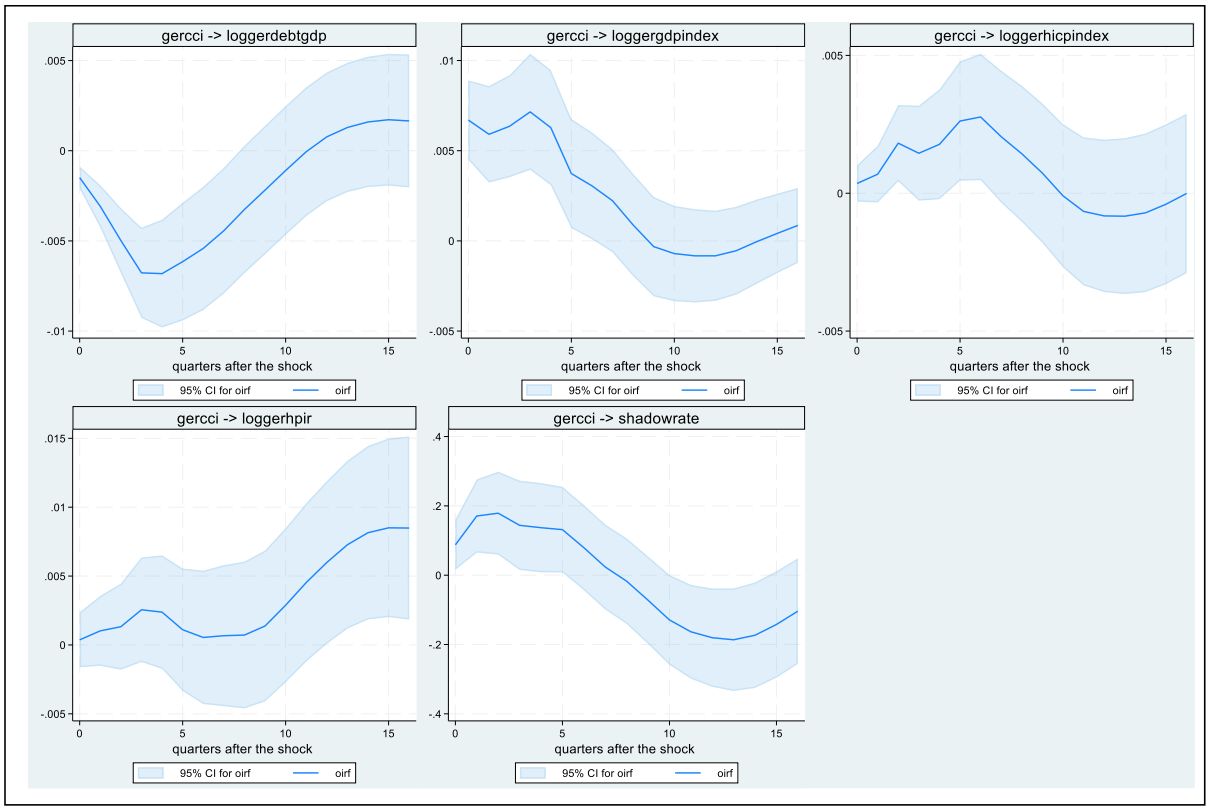

Figure 6. Robustness test: The effect of consumer confidence shock in Germany (alternative definition of household debt)

Source: Authors own calculations.

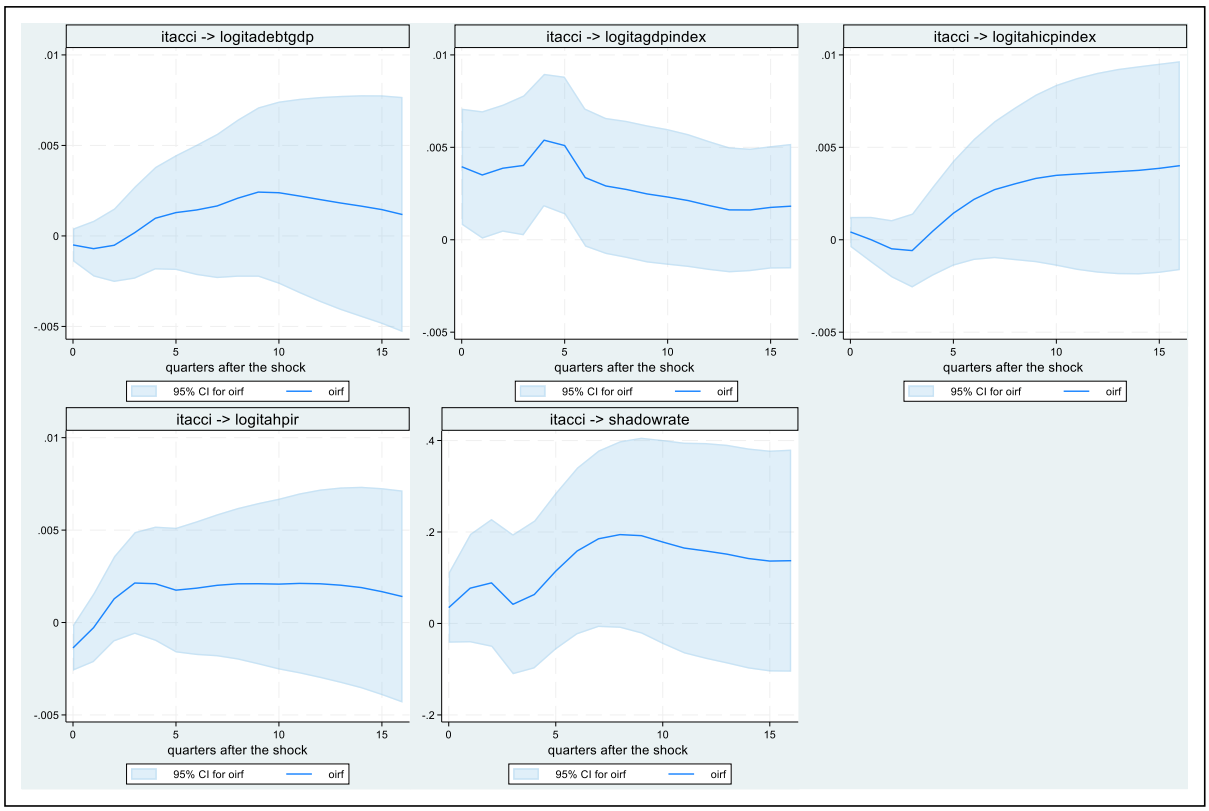

Figure 7. Robustness test: The effect of consumer confidence shock in Italy (alternative definition of household debt)

Source: Authors own calculations.

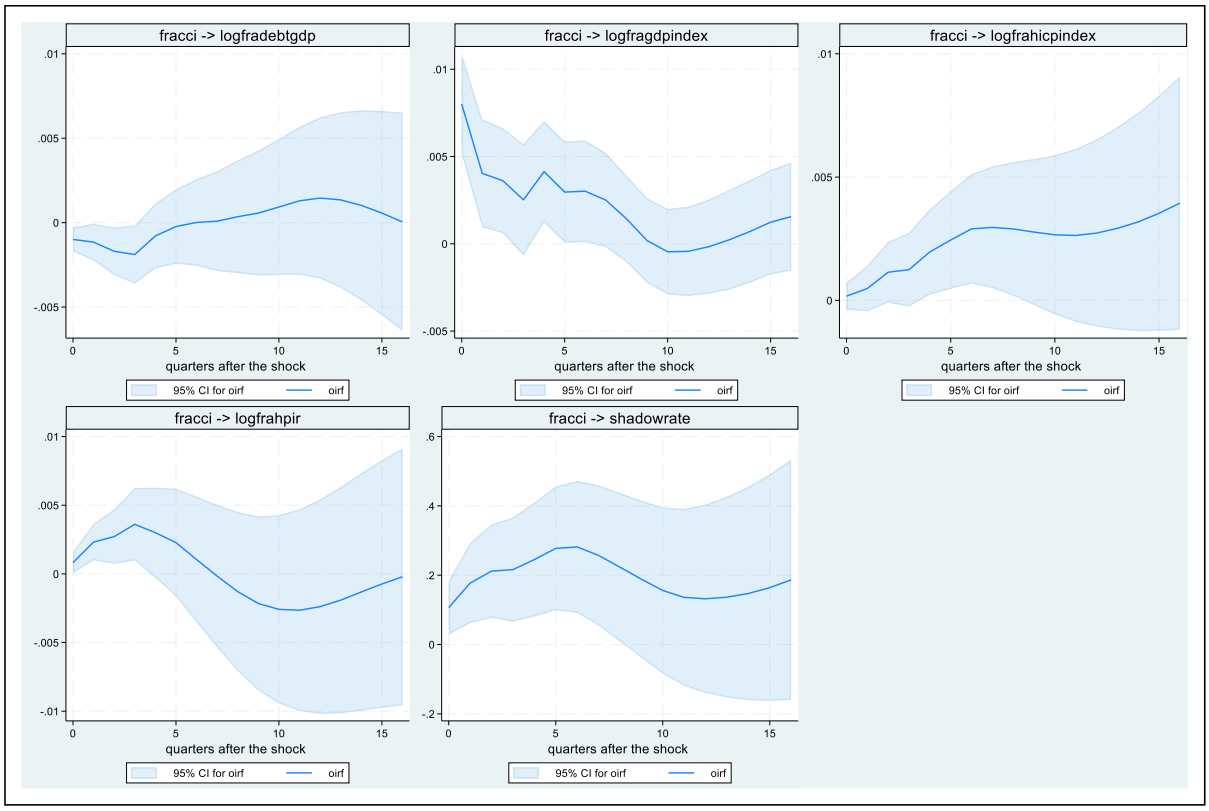

Figure 8. Robustness test: The effect of consumer confidence shock in France (alternative definition of household debt)

Source: Authors own calculations.

5. Conclusion

In this paper, we empirically analyze the effect of consumer confidence shocks on household debt using time series data for Germany, Italy, and France, respectively, covering the period from 1999Q1 to 2024Q1. Our study highlights the role of consumer confidence (as measured by the DG ECFIN business and consumer surveys) on household debt behaviour. Our results indicate that household debt responses to consumer confidence shocks are heterogeneous: negative (i.e. reduction) in Germany, positive (i.e. increase) in Italy, and not significant in France. Additionally, in Germany, a positive shock to consumer confidence results in an immediate increase in GDP, while the ECB's monetary policy rate responds with a one-quarter lag. House prices exhibit a significant and positive response to the shock only after a period of three and a half years. Furthermore, in Italy, a positive shock to consumer confidence results in a significant increase in both GDP and house prices, with the effects manifesting initially following the shock and after a delay of three quarters, respectively. In France, GDP, house prices and ECB's monetary policy shadow rate experience a significant increase immediately following the shock, while HICP responds with a delay of six quarters. However, in both Germany and Italy, the response of the HICP remains non-significant throughout the observed period. The ECB's monetary policy response is non-significant in Italy, in contrast to the significant effects observed in Germany and France. By examining consumer confidence alongside traditional (macro)economic fundamentals, our results suggest that psychological factors, as manifested by consumer confidence, can influence household debt dynamics immediately after the shocks in Germany, but with a delay in Italy. Finally, our results emphasize the critical role of consumer confidence in shaping household debt dynamics. By integrating consumer confidence with traditional macroeconomic fundamentals, our findings demonstrate that psychological factors, as reflected in consumer confidence, are important determinants of household debt in both Germany and Italy, though not in France.

References

Alfaro, R., & Gallardo, N. (2012). The determinants of household debt default. Economic Analysis Review, 27(1), 27-54.

Alter, A., Xiaochen Feng, A., & Valckx, N. (2018). Understanding the Macro-Financial Effects of Household Debt: A Global Perspective. Available at: <https://www.imf.org/en/Publications/WP/Issues/2018/04/06/Understanding-the-Macro-Financial-Effects-of-Household-Debt-A-Global-Perspective-45744>[Accessed on July 2024].

Angelico, C.(2019). Household Expectations and the Credit Cycle. Available at: <https://ssrn.com/abstract=3491685>[Accessed on July 2024].

Beaudry, P., & Portier, F. (2014). News-driven business cycles: Insight and challenges. Journal of Economic Literature 52(4), 993–1074.

Brown, S., Garinko, G., Taylor, K. & Price, W. (2005). Debt and Financial Expectations: An individual and household level analysis. Economic Inquiry,43(1), 100 – 120.

Brown, S., Garino, G., & Taylor, K. (2008). Mortgages and Financial Expectations: A Household-Level Analysis. Southern Economic Journal74, 857 – 878.

Borsch-Supan, A. (2003). Life-Cycle Savings and Public Policy: A Cross-National Study of Six Countries. Elsevier Science. Available at: <https://books.google.si/books?id=1uh4Dob7uNoC>[Accessed on September 2024].

Canova, F., & Ciccarelli, M. (2009). Estimating Multicountry VAR Models. International Economic Review, 50(3), 929-959.

Carroll, C. D., Fuhrer, J. C., & Wilcox, D. W. (1994). Does Consumer Sentiment Forecast Household Spending? If So, Why? The American Economic Review, 84(5), 1397-1408.

Coletta, M., De Bonis, R., & Piermattei, S. (2019). Household Debt in OECD Countries. The Role of Supply-Side and Demand-Side Factors. Social Indicators Research, 143(3), 1185-1217.

Daskalopolou, I. (2023). Encyclopedia of Quality of Life and Well-Being Research, Second Edition. Consumer Confidence Index. Available at: <https://link.springer.com/referencework/10.1007/978-3-031-17299-1>[Accessed on September 2024].

ECB (2000): Seasonal Adjustment of Monetary Aggregates and Hicp for The Euro Area.Available at: <https://www.ecb.europa.eu/pub/pdf/other/sama0008en.pdf>[Accessed on May 2024].

ECB. (2024). Euro area economic and financial developments by institutional sector, Statistical Release. Available at: <https://www.ecb.europa.eu/press/stats/ffi/html/ecb.eaefd_full2024q1~4e13444d3f.en.html>[Accessed on July 2024].

Enache, C. (2022). Macroeconomic Determinants of Household Indebtedness in Romania: An Econometric Approach. Journal of Social and Economic Statistics, 11(1-2), 102-117. <https://doi.org/doi:10.2478/jses-2022-0006>[Accessed on May 2024].

Enders, W. (1995). Applied Econometric Time Series. New York: John Wiley & Son, Inc.

ESA 2010. (2013). European system of accounts - ESA 2010. Luxembourg: Publications Office of the European Union. Available at: <https://ec.europa.eu/eurostat/documents/3859598/5925693/KS-02-13-269-EN.PDF>[Accessed on July 2024].

Eurostat (2024a): Financial balance sheets - quarterly data.Available at: <https://ec.europa.eu/eurostat/databrowser/view/nasq_10_f_bs__custom_12281892/default/table->[Accessed on July 2024].

Eurostat (2024b): Non-financial transactions - quarterly data.Available at: <https://ec.europa.eu/eurostat/databrowser/view/nasq_10_nf_tr__custom_12244880/default/table>[Accessed on July 2024].

Eurostat (2024c): Handbook on Seasonal Adjustment.Available at: <https://ec.europa.eu/eurostat/en/web/products-manuals-and-guidelines/-/ks-gq-18-001>[Accessed on July 2024].

Eurostat (2024d): GDP and main components (output, expenditure and income).Availabe at: <https://ec.europa.eu/eurostat/databrowser/view/namq_10_gdp__custom_12221104/default/table>[Accessed on July 2024].

Eurostat (2024e): Harmonised Index of Consumer Prices (HICP) Methodological manual – 2024 edition.Available at: <https://ec.europa.eu/eurostat/en/web/products-manuals-and-guidelines/w/ks-gq-24-003>[Accessed on July 2024].

Eurostat (2024f): HICP - monthly data (index).Availabe at: <https://ec.europa.eu/eurostat/databrowser/view/prc_hicp_midx__custom_12221285/default/table>[Accessed on July 2024].

European Union. (2006). Joint Harmonised EU Programme of Business and Consumer Surveys. EUR-Lex: 2006/C 245/03.

European Commission. (2024a). Economy and Finance, Economic forecast and surveys, Business and consumer surveys.Available at: <https://economy-finance.ec.europa.eu/economic-forecast-and-surveys/business-and-consumer-surveys/download-business-and-consumer-survey-data/time-series_en>[Accessed on July 2024].

European Commission. (2024b). The Joint Harmonised EU Programme of Business and Consumer Surveys, User Guide (updated January 2024).Available at: <https://economy-finance.ec.europa.eu/document/download/4f162b92-e654-4cef-beed-38960dae1b09_en?filename=bcs_user_guide.pdf>[Accessed on July 2024].

Friedman, M. (1957). A Theory of the Consumption Function. Princeton University Press.

Gric, Z., Ehrenbergerova, D., & Hodula, M. (2022). The power of sentiment: Irrational beliefs of households and consumer loan dynamics. Journal of Financial Stability, 59, 100973.

Hamilton, J. D. (1994). Time Series Analysis. Princeton: Princeton University Press.

Johansen, S. (1995). Likelihood-Based Inference in Cointegrated Vector Autoregressive Models. Oxford: Oxford University Press.

Katona, G. (1968). On the function of behavioral theory and behavioral research in economics. American Economic Review, 58, 146–149.

Khan, H., Rouillard, J. F., & Upadhayaya, S. (2019). Consumer Confidence and Household Investment. Available at: <https://carleton.ca/economics/wp-content/uploads/cewp19-06.pdf>[Accessed on May 2024].

Kłopocka, A. (2017). Does Consumer Confidence Forecast Household Saving and Borrowing Behaviour? Evidence from Poland. Social Indicators Research 133(2), 693–717.

Krippner, L. (2015). Zero Lower Bound Term Structure Modeling, A Practitioner's Guide. US: Palgrave Macmillan New York.

Krippner, L. (2024). LJK Macro finance analysis – Visitors.Available at: <https://www.ljkmfa.com/visitors/>[Accessed on May 2024].

Kozina, M., & Tartamella, F. (2019). International Association for Research in Income and Wealth, Past Conferences. Available at:<http://old.iariw.org/moscow/Kozina-final.pdf>[Accessed on May 2024].

Lane, P. R. (2023). The banking channel of monetary policy tightening in the euro area.Remarks by Philip R. Lane, Member of the Executive Board of the ECB, at the Panel Discussion on Banking Solvency and Monetary Policy. Availabe at: <https://www.ecb.europa.eu/press/key/date/2023/html/ecb.sp230712~d950906f00.en.html>[Accessed on September 2024].

Leduc & Sill, (2013). Expectations and Economic Fluctuations: An Analysis Using Survey Data. The Review of Economics and Statistics 95(4), 1352–1367.

Lombardi, M, Mohanty, M., & Shim, I. (2017). The real effects of household debt in the short and long run. Empirical Economics 63, 1887–1911.

Lütkepohl, H. & Krätzig, M. (2004). Applied Time Series Econometrics. New York: Cambridge University Press.

Lütkepohl, H. (2005). New Introduction to Multiple Time Series Analysis. Springer.

Malinen, T. (2016). Does income inequality contribute to credit cycles? The Journal of Economic Inequality, 14(3), 309-325.

Matsusaka, J. G., & Sbordone, A. M. (1995). Consumer Confidence and Economic Fluctuations. Economic Inquiry, 33(2), 296-318.

Meng, X., Hoang, N. T., & Siriwardana, M. (2013). The determinants of Australian household debt: A macro level study. Journal of Asian Economics, 29, 80-90.

Mian, A., Sufi, A., & Verner, E. (2015). Household Debt and Business Cycles Worldwide. Available at: <https://EconPapers.repec.org/RePEc:nbr:nberwo:21581>[Accessed on May 2024].

Modigliani, F., & Brumberg, R. (1954). Utility Analysis and the Consumption Function: An Interpretation of Cross-Section Data. In Post-Keynesian Economics, edited by Kenneth K. Kurihara, 388–436. Rutgers University Press.

Moore, G. L., & Stockhammer, E. (2018). The drivers of household indebtedness reconsidered: An empirical evaluation of competing arguments on the macroeconomic determinants of household indebtedness in OECD countries. Journal of Post Keynesian Economics, 41(4), 547–577.

OCED. (2024). OECD Data Explorer – Analytical house prices indicators.Available at: <https://dataexplorer.oecd.org/vis?lc=en&tm=DF_HOUSE_PRICES&pg=0&snb=1&vw=tb&df[ds]=dsDisseminateFinalDMZ&df[id]=DSD_AN_HOUSE_PRICES%40DF_HOUSE_PRICES&df[ag]=OECD.ECO.MPD&df[vs]=1.0&pd=%2C&dq=.Q.RHP.&to[TIME_PERIOD]=false>[Accessed on July 2024].

Sims, C. A. (1980). Macroeconomics and Reality. Econometrica 48(1), 1–48.

Sims, C. A., Stock, J. H., & Watson, M. W. (1990). Inference in Linear Time Series Models with Some Unit Roots. Econometrica, 58(1), 113-144.

Stiglitz, J. E., & Weiss, A. (1981). Credit Rationing in Markets with Imperfect Information. The American Economic Review, 71(3), 393-410.

Stock, J. H., & Watson, M. (2001). Vector Autoregressions. Journal of Economic Perspectives, 15(2), 101 – 115.

SNA 2008. (2009). System of National Accounts 2008. Available at: <https://unstats.un.org/unsd/nationalaccount/docs/SNA2008.pdf>[Accessed on May 2024].

Throop, A. W. (1992). Consumer Sentiment: Its Causes and Effects.Economic Review, Federal Reserve Bank of San Francisco, 1, 35-59.

Van Aarle, B. & Moons, C. (2017). Sentiment and Uncertainty Fluctuations and Their Effects on the Euro Area Business Cycle. Journal of Business Cycle Research 13(2), 225 –251.

Vanlaer, W., Bielen, S., &Marneffe, W. (2020). Consumer Confidence and Household Saving Behaviors: A Cross-Country Empirical Analysis. Social Indicators Research,147(2), 677-721.

Zabai, A. (2017). Household Debt: Recent Developments and Challenges. Available at: <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3082582>[Accessed on May 2024].

Wildauer, R. (2016). Determinants of US Household Debt: New Evidence from the SCF. Working Paper 1608: Greenwich Papers in Political Economy, 18277. Available at: <https://www.postkeynesian.net/downloads/working-papers/PKWP1608.pdf>[Accessed on August 2024].