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Sentiment Driven Loans

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Sentiment Driven Loans

ABSTRACT

We study the effect of consumer sentiment on bank lending in a panel of eleven European economies that have experienced significant credit expansion in recent decades. Using standardized surveybased consumer data, we distinguish between the sentiment about i) current and ii) future (expected) economic conditions. Nonlinear machine-learning techniques allow us to improve the identification of exogenous sentiment shocks by using a large set of macro-financial variables. The component of sentiment that is unexplained by economic conditions reflects exogenous (or irrational) sentiment shocks. Using a local projections approach, we show that positive sentiment shocks lead to both short- and long-term increases in housing loans, with little effect on consumer loans. We also find that shocks to sentiment related to future economic conditions have a stronger effect on bank lending than shocks to present sentiment do. Shocks to sentiment explain up to 10% of housing loan growth over the next two years following the shock and are most pronounced under persistently loose monetary policy. Finally, we also show that sentiment has implications for financial stability, as positive sentiment shocks increase the vulnerability of the banking system.

KEYWORDS: sentiment, bank lending, monetary policy, machine learning, bank leverage
JEL CLASSIFICATION: E52, G21, C40

Úvery ovplyvnené sentimentom

ABSTRAKT

V tomto článku študujeme vplyv spotrebiteľského sentimentu na poskytovanie bankových úverov v paneli jedenástich európskych ekonomík, ktoré v posledných desaťročiach zaznamenali výraznú úverovú expanziu. Pomocou štandardizovaných spotrebiteľských prieskumov rozlišujeme medzi sentimentom, ktorý sa týka i) aktuálnych a ii) budúcich (očakávaných) ekonomických podmienok. Nelineárne techniky strojového učenia nám umožňujú zlepšiť identifikáciu exogénnych šokov sentimentu využitím rozsiahleho súboru makrofinančných premenných. Komponent sentimentu, ktorý nie je vysvetlený ekonomickými podmienkami, odráža exogénne (alebo iracionálne) šoky sentimentu. Prostredníctvom lokálnych projekcií ukazujeme, že pozitívne šoky sentimentu vedú ku krátkodobému aj dlhodobému nárastu hypotekárnych úverov, pričom majú len malý vplyv na spotrebiteľské úvery. Zistili sme, že šoky sentimentu týkajúce sa budúcich ekonomických podmienok majú silnejší vplyv na bankové úverovanie ako šoky súčasného sentimentu. Šoky sentimentu vysvetľujú až 10\% rastu hypotekárnych úverov v priebehu dvoch rokov po šoku a sú najvýraznejšie pri pretrvávajúcej uvoľnenej menovej politike. Nakoniec tiež ukazujeme, že sentiment má dôsledky pre finančnú stabilitu, keďže pozitívne šoky sentimentu zvyšujú zraniteľnosť bankového systému.

KĽÚČOVÉ SLOVÁ: sentiment, dôvera, bankové úvery, menová politika, strojové učenie, finančná páka bánk
JEL KLASIFIKÁCIA: E52, G21, C40

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Introduction

A large body of empirical evidence links positive sentiment with improvements in real economic activity. However, two main competing hypotheses have been proposed to explain this link. First, positive sentiment does not have a causal effect on the real economy—it merely contains some information that helps predict future economic developments (Barsky and Sims, 2012; Beaudry and Portier, 2014). Second, positive sentiment can affect economic developments, either by creating a self-fulfilling feedback loop (Benhabib et al., 2016; Constantinides et al., 2025) or by easing financial constraints (McLean and Zhao, 2014). As these channels are difficult to disentangle, no consensus exists regarding the macroeconomic consequences of sentiment.

In this paper, we focus on one of the channels through which sentiment can influence economic activity: We study how consumers' beliefs about the state of the economy—their sentiment—affect bank lending. Since substantial credit growth has been identified as an important driver of financial instability (Jorda et al., 2011; Schularick and Taylor, 2012), we also extend the analysis to the consequences of sentiment for the stability of the banking sector. We follow a growing body of research that relies on survey-based sentiment measures (Carroll et al., 1994; Barsky and Sims, 2012; Beaudry and Portier, 2014; Gric et al., 2022; Constantinides et al., 2025). Such direct sentiment measures provide a broad and aggregate perspective on economic agents' view of the state of the economy (Caglayan and Xu, 2016). Survey-based sentiment indicators encompass information about not only past economic development but also the current and future behaviour of economic agents (Gric et al., 2022). Moreover, they contain information about agents' perceptions and expectations of future economic conditions (DG ECFIN, 2024) and can signal elevated levels of uncertainty (Vuchelen, 2004).

Several studies have already shown a link between such sentiment indicators and economic activity. For instance, Matsusaka and Sbordone (1995), Batchelor and Dua (1998) and Christiansen et al. (2014) report that the Michigan Index of Consumer Sentiment could be a useful tool for forecasting economic fluctuations, while Beaudry et al. (2011) suggest that swings in consumer optimism and pessimism are important drivers of business cycles. Moreover, Barsky and Sims (2012) find that consumer confidence indicators containing fundamental news can be used as a predictor of future economic fundamentals, whereas the overly optimistic or pessimistic moods of consumers do not predict business cycle fluctuations. Constantinides et al. (2025) identify a heterogeneous effect of sentiment on economic growth: The effect of sentiment on economic growth is more pronounced in less advanced economies than in major advanced economies because, owing to the less efficient financial markets in these countries, economic agents have greater difficulty distinguishing sentiment from fundamentals.

In this paper, we argue that such surveys could also have the potential to reflect the expectations of economic agents regarding economic developments, which in turn might influence agents' borrowing behaviour. This hypothesis could be supported by the life-cycle hypothesis of Modigliani and Brumberg (1954), as it implies that individuals plan their consumption decisions given their expectations about income. Households may wish to finance their current consumption with external financing sources if they are optimistic about their expected future income. Negative sentiment may indicate greater uncertainty, which could in turn negatively impact the borrowing decisions of households (Košťálová et al., 2022). The life-cycle model of Exler et al. (2025) indicates that over-optimists tend to overestimate their ability to repay a loan and underestimate default costs, leading them to borrow too much. Since an uncertain economic environment has been shown to lead to precautionary savings (Mody et al., 2012), negative sentiment might lead to a reduction in households' consumption spending (Anastasiou et al., 2023) and, by extension, a reduction in credit demand.

To study the effect of sentiment on bank lending, we use monthly data covering the period from January 2008 to March 2025 across 11 Central and Eastern European (CEE) economies that have experienced significant credit expansion over the past two decades. We construct our

survey-based sentiment indicator on the basis of the aggregated responses of consumers from harmonised consumer surveys. Survey-based sentiment indicators are often constructed on the basis of questions that reflect both households' views of the current state of the economy and their expectations of future economic developments (Gric et al., 2022). However, the forwards-looking component of sentiment, reflected in households' expectations about the future, is arguably more important for households' decision-making than the more backwards-looking component of sentiment that is reflected in households' assessment of the current state of the economy (Bram and Ludvigson, 1998). To test this hypothesis, we construct two separate sentiment indices that reflect consumers' sentiments about current (past) economic conditions and about future economic conditions, as we expect that borrowing behaviour, a commitment linked to the future household budget, should be strongly influenced by expectations about economic conditions.

An important empirical challenge lies in the identification of the causal effect of sentiment. This inherent difficulty in disentangling the effect of sentiment from related developments, such as aggregate demand shocks, could also explain the lack of consensus regarding the relationship between sentiment and economic fundamentals. To address this identification challenge, we propose a novel approach in which we use several machine learning techniques to identify shocks to consumer sentiment that are orthogonal to economic conditions. The machine learning models are used to predict consumer sentiment on the basis of available information about economic fundamentals. The unpredicted component of sentiment is then taken as sentiment unrelated to economic fundamentals.[2] Next, we use the local projections framework to examine the causal effect of sentiment shocks.

The literature on the drivers of credit growth is extensive, and different variables are identified as drivers of credit growth. These include interest rates (Hofmann, 2001; Elekdag and Wu, 2013; Gozgor, 2018), unemployment rates (Nkusu, 2011; Louzis et al., 2012; Chaibi and Ftiti, 2015), house prices (Mian and Sufi, 2011; Anundsen and Jansen, 2013; Cloyne et al., 2019), and economic growth (Aisen and Franken, 2010; Duenwald et al., 2006; Gozgor, 2018). In addition to considering the "traditional" set of credit drivers, a recent body of literature uses measures of uncertainty or sentiment to model credit growth. Several studies have used the economic policy uncertainty (EPU) index of Baker et al. (2016) as a measure of uncertainty to examine its impact on credit (Bordo et al., 2016; Caglayan and Xu, 2019; Danisman et al., 2020; Košťálová et al., 2022).

Nevertheless, the role of sentiment in influencing bank lending remains relatively underexplored, with only a few studies related to ours: Delis et al. (2014) investigate how banks' lending behaviour changes during anxious periods, when economic agents' expectations worsen but the economy is not in recession. They find that higher anxiety decreases the bank loan supply. Similarly, Caglayan and Xu (2016) show that changes in the perceptions of economic agents and their sentiment volatility have a significant effect on the provision of credit by banks. While the previous studies focused on bank supply, Košťálová et al. (2022) conclude that disaggregated survey-based consumer sentiment may be more relevant and appears to predict the creation of new loans. The study most closely related to our is that of Gric et al. (2022), who study the effect of sentiment on consumer loan growth using a sample that covers 15 countries located mostly in Western Europe. They decompose sentiment into rational and irrational components. The rational component is driven by macroeconomic fundamentals, whereas the irrational component serves as a proxy for excessive optimism or pessimism. They find that irrational sentiment has an asymmetric effect on bank lending, with a positive effect on consumer loans occurring only during upwards stages of the business cycle.

We extend the literature in several ways: First, we distinguish between the effects of consumer sentiment on consumer loans and on housing loans. Consumer loans serve as a proxy for financing household consumption, whereas housing loans are used to finance more long-term in-

[2] Gric et al. (2022), who use a simple linear regression to identify orthogonal sentiment shocks, refer to these shocks as *irrational sentiment* since they are unrelated to economic fundamentals.

vestments. We find that an unexpected increase in sentiment is more likely to be associated with a large short- to long-term (up to 24 months) increase in housing loans than with such an increase in consumer loans . Second, our approach to identifying sentiment shocks is based on decomposing the corresponding measure of consumer sentiment into a sentiment component driven by economic fundamentals and a sentiment component that is orthogonal to fundamentals. We call the latter component pure sentiment, and we use it as our proxy for sentiment shocks. In contrast to earlier studies, such as Baker and Wurgler (2006), Gric et al. (2022), Anastasiou et al. (2023), and Constantinides et al. (2025), we use machine learning techniques and combination forecasts to identify the fundamental-driven (or rational) component of consumer sentiment. This approach allows us to reduce model choice uncertainty, use a broader set of lagged fundamentals (including past borrowing activity and seasonal effects) in the data-generating process of consumer sentiment and thus address reverse causality and omitted-variable bias, and to some extent attenuate the potential bias from generated regressors (see Battaglia et al., 2024). The resulting forecast errors serve as a proxy for pure (or irrational) sentiment. The application of machine learning techniques enables us to sharpen the identification of sentiment shocks, as with machine learning techniques, we can use all the available information about economic fundamentals to identify the fundamental-driven component of sentiment and to exclude the sentiment that is unrelated to economic fundamentals. Third, we disaggregate consumer sentiment based on the assumption that sentiment about the present/past and sentiment about the future play different roles in influencing bank lending. Our results confirm that changes in lending are more strongly associated with unexpected changes in sentiment related to future economic conditions than with shocks to sentiment related to present/past economic conditions. The observed effects of positive sentiment shocks are relatively large and can account for up to one-tenth of the expected changes in housing loans during the 2 years following the shock. Moreover, we find that the greater the difference between the shocks to future and present/past sentiment is, the stronger the impact of future sentiment. Fourth, while we find that sentiment is not specific to highly uncertain periods, such as the Global Financial Crisis or the COVID-19 pandemic in 2020, a persistently loose monetary policy stance exacerbates the effect of sentiment on bank lending. Fifth, we link unexpected increases in sentiment – positive sentiment shocks – with increased bank leverage, which suggests that sentiment might have adverse consequences for financial stability. Thus, we expand the literature on the drivers of financial instability (Beck et al., 2006; Laeven and Levine, 2009; Fang et al., 2014; Horvath and Vasko, 2016; Schularick et al., 2021; Chabot and Bertrand, 2023; Grimm et al., 2023; Jimenez et al., 2025) by identifying another determinant of financial (in)stability.

The structure of the remainder of this paper is as follows: Section 2 introduces our data. Section 3 describes the methodology for constructing our measure of consumer sentiment and estimating the effect of sentiment shocks on bank lending. The results are reported in Section 4, while Section 5 concludes the paper and formulates several policy implications. Additional results can be found in the Appendix.

1 Data

Our study uses monthly data from eleven Central and Eastern European (CEE) countries, i.e., Slovakia (SK), the Czech Republic (CZ), Hungary (HU), Poland (PL), Slovenia (SI), Croatia (HR), Estonia (EE), Lithuania (LT), Latvia (LV), Bulgaria (BG) and Romania (RO), which collectively represented approximately 100 million people Eurostat (2025) as of 2024, or 22% of the total population of the European Union. The countries in our sample have experienced comparable socioeconomic developments, as they are all former centrally planned economies that underwent the transition process to a free market economy, a process marked by the restructuring of the banking sector, privatization, financial liberalization, and the development of property markets starting in the 1990s. In all eleven countries, there has been an unprecedented increase in the provision of household credit

over the past three decades, while financial development persistently lags behind that of the rest of Europe (Égert et al., 2006; Tchaidze and Adarov, 2011; Lahnsteiner, 2020; Engler et al., 2024).

Our monthly data for consumer and housing loans end in March 2025, although they begin at different dates for each country. For the panel analysis of the effect of sentiment on bank lending, the data start in January 2008 for Slovakia, the Czech Republic, Hungary, Slovenia, Lithuania, Bulgaria, and Romania; in April 2009 for Poland; in February 2008 for Estonia; in January 2011 for Croatia; and in October 2010 for Latvia. We create two indices of consumer sentiment about the present and the future on the basis of a harmonised consumer survey published by the Directorate-General for Economic and Financial Affairs (DG ECFIN). The advantage of consumer survey data is their high frequency and harmonisation across countries of the European Union. See Tables A1 and A2 for details of the questions used to construct the sentiment indices. For the decomposition of sentiment (see next section), the data on sentiment and the selected predictors used for this decomposition start in January 2002 for each country, with the exception of Croatia, where sentiment surveys begin in April 2005.

2 Methodology

In this section, we first outline the approach we use to identify sentiment shocks. Next, we introduce our empirical strategy to identify the effect of sentiment shocks on bank lending.

2.1 Sentiment Shock Identification

2.1.1 Sentiment Decomposition

To construct our measure of consumer sentiment, we use the data from the harmonised consumer survey. On the basis of respondents' survey answers, we construct two sentiment indices – one for present sentiment (S_t^P) and one for future sentiment (S_t^F). However, several previous studies show that such sentiment measures could also reflect economic fundamentals (Anastasiou et al., 2023; Baker and Wurgler, 2006; Baker et al., 2012; Constantinides et al., 2025; Gric et al., 2022). Therefore, we follow these earlier studies and decompose our sentiment measure into the sentiment explained by economic fundamentals and the component of sentiment that is orthogonal to fundamentals:

$$S_t = S_t^E + S_t^\perp \tag{1}$$

where S_t is either of our two consumer sentiment indices ($S_t \in (S_t^P, S_t^F)$), S_t^E is the sentiment component driven by economic fundamentals, which we refer to as fundamental-driven or news-driven sentiment, and $S_t^\perp$ is the sentiment component that is orthogonal to economic fundamentals. Following Constantinides et al. (2025), we refer to this component as the pure sentiment.[3] At a high level, the decomposition of sentiment into the fundamental-driven and pure sentiment components can be represented as follows:

$$S_t = f(\boldsymbol{Z}|I_{t-1}) + \epsilon_t^s \tag{2}$$

where $\boldsymbol{Z}$ is a matrix of economic fundamentals that can predict consumer sentiment and I_{t-1} denotes an information set; i.e., all the data are known one month before we observe the sentiment at time t. Finally, the function $f(.)$ represents the predicted values from a given model. The predicted values from equation 2 can be perceived as fundamental-driven sentiment ($f(\boldsymbol{Z}|I_{t-1}) \equiv S_t^E$), while the residuals serve as our proxy for pure sentiment ($\epsilon_t^s \equiv S_t^\perp$).

Since the fundamental drivers of consumer sentiment might differ across countries, we estimate the model given in equation 2 separately for each country in our sample using multiple lags of

[3] Gric et al. (2022) denote this sentiment component as *irrational sentiment*.

the following variables: i) changes in consumer loans, ii) changes in housing loans, iii) future sentiment, iv) past sentiment, v) unemployment rate, vi) percentage changes in the harmonised index of consumer prices, vii) Euro Area shadow rate, viii) current account deficit to GDP, ix) changes in the industrial production index, x) changes in the house price index, xi) interest rates on new household loans, xii) the macroprudential policy index[4], xiv) changes in the exchange rate to EUR (except for Slovakia, Slovenia and Estonia), xiv) euro area composite indicator of systemic stress, xv) implied volatility index (VIX), xvi) monthly EUREX realized daily Volatility, xvii) changes in the industrial production of the Euro area, and xviii) linear time trend. The machine learning models utilize lagged values of orders 1, 2, 3, and 12 to account for short-term persistence and potential seasonal effects.

The broader set of lagged economic variables and the nonlinear modelling framework address potential concerns related to reverse causality and omitted-variable bias. Specifically, in CEE countries, real estate represents a substantial share of households' wealth. Therefore, an increase in the value of assets might also drive sentiment. We address such concerns by using past changes in consumer behaviour, housing loans, the house price index, the unemployment rate, and interest rates–all potential drivers or predictors of house prices (e.g., Delis et al. (2014); Gric et al. (2022)). Moreover, the eighteen economic fundamentals with four lags and nonlinear combinations can proxy for other important variables that we might be missing, while out-of-sample cross-validation and final averaging prevent overfitting of our models. Our setup is also likely to mitigate potential concerns related to the sources of loan provision, whether they are driven by the supply or demand side of the market, as we likely capture both in a time-varying manner given the re-estimation of model parameters after each month. Finally, we mitigate the generated regressor bias by using multiple models, averaging, and cross-validation, which is common in the literature (Battaglia et al., 2024), since averaging attenuates the measurement error (from generated regressors) relative to the sampling error. Moreover, sentiments are very persistent, which should make any bias (if present) negligible.

2.1.2 Sentiment Forecasts

To approximate the unknown function $f(.)$, we use a random walk model as our benchmark and three data-driven methods to estimate the equation 2. As the first method, we use penalized regression models that encompass the LASSO, Ridge, and Elastic Net penalties, with the model minimizing the following expression:

$$\underset{\hat{\boldsymbol{\beta}}}{min} \rightarrow \sum_{i=1}^{n}(S_t - \sum_{k=0}^{K}\hat{\beta}_k Z_{k|I_{t-l}})^2 + \lambda\left(\alpha\sum_{k=1}^{K}|\beta_k| + (1-\alpha)\sum_{k=1}^{K}\beta_k^2\right) \tag{3}$$

where S_t is the given measure of sentiment and $Z_{k|I_{t-l}}$ are lagged fundamentals (with $l = 1, 2, 3, 12$). The two hyperparameters are $\lambda > 0$, which is the penalty term, and $\alpha \in (0.0, 0.1, ..., 0.9, 1.0)$, where $\alpha = 1$ is the LASSO penalty of Tibshirani (1996), $\alpha = 0$ is the Ridge penalty of Hoerl and Kennard (1970b,a), and the remaining α values correspond to the Elastic Net penalty of Zou and Hastie (2005). We consider 100 different $\lambda \in \left(\ln 10^{-4} \times \lambda_{max}, \ln \lambda_{max}\right)$, where λ_{max} is selected so that it is the highest λ (across different α values as well), for which all the coefficients (except the intercept) are penalized to 0 on an initial sample of the first 36 observations.

The second model is the random forest of Breiman (2001), which uses B different bootstrap subsamples to estimate B regression trees using the recursive binary splitting algorithm that minimizes the mean square error. The trees are grown until a given node has fewer than 5 observations, which is the minimum required for a split. We use two hyperparameters: i) the trees are decorrelated by using a random selection of $N \in (2, 4, 6, 8, 10)$ variables that are considered for splitting a

[4]An index indicating cumulative change in the tightening (+1) or loosening (-1) of macroprudential policy measures as indicated via changes in the countercyclical capital buffer (effective date), capital conservation buffer (effective date), loan-to-value ratio and debt service-to-income ratio.

node (out of 69 explanatory variables) and ii) the number of trees $(250, 500, 1000, 2000)$. Considering the use of the prediction $p(T_{t,b}(\boldsymbol{Z}|I_{t-1}))$ from a tree b (from a given bootstrap sample) at time t, the random forest prediction is averaged across all the trees generated from different bootstrap samples:

$$f^{B}_{RF,t}(x) = \frac{1}{B}\sum_{b=1}^{B} p(T_{t,b}(\boldsymbol{Z}|I_{t-1})) \tag{4}$$

The third model is the boosted regression tree. Given a set of variables $\boldsymbol{Z}|I_{t-1}$ and sentiment S_t, we estimate a regression tree denoted by $T^0_t(S_t, \boldsymbol{Z}|I_{t-1})$. The predicted observations are given by $\hat{S}_{t,T^0}$, and the corresponding errors are $R^0_t = S_t - \hat{S}_{t,T^0}$. An updated prediction is given by $S^{b=1}_t = \hat{S}_{t,T^0} + \eta R^0_t$, where $\eta > 0$ is the learning rate. A sequence ($b = 1, 2, ..., B$) of regression trees follows, where the subject of interest is residuals from the previous model. We consider $\eta \in (0.30, 0.10, 0.01, 0.001)$ as the potential learning rate, $B \in 250, 500, 1000$ as the number of trees, and $D \in (3, 6, 9)$ as the maximum depth of the tree; all hyperparameters.

The hyperparameters are estimated for each model using a full-grid search in an expanding estimation window size that starts with 36 months. An additional 12 months is used to observe the out-of-sample performance, measured by the mean square error of the model under different hyperparameter settings. The combination of hyperparameters that leads to the lowest mean-square error is selected for the next period predictions. The first true out-of-sample prediction is the 49^{th} observation and is given as a winsorized average of the four forecasts (random walk, EN, random forest, and boosted regression tree), where the highest and lowest forecasts are removed. Then, all the models are re-estimated, the mean-square errors over the past 12 months are re-evaluated, and a new suitable combination of hyperparameters may be employed. The use of the average to estimate $f(\boldsymbol{Z}|I_{t-1})$ is motivated by the combination forecasting literature popularized as early as Bates and Granger (1969); Granger and Ramanathan (1984) and more recently by Timmermann (2006). This literature argues that averaging diversifies against model choice uncertainty, and a suitable ensemble can lead to lower (mean-square) forecast errors, provided that individual forecasts are unbiased and exhibit low correlation.

2.2 Local Projections

To evaluate the effect of sentiment on bank lending, we apply the local projections (LP) approach of Jorda (2005). This approach enables us to generate the impulse response of bank loans to a sentiment shock by estimating a separate regression for each forecasting horizon h, with each of these regressions being conditional on a set of covariates in the initial period. We begin our analysis by estimating the following equation for a panel of the 11 Central European countries in our sample:

$$\begin{aligned} y_{i,t+h} - y_{i,t} = \alpha^h_i + \beta^h_1 \epsilon^s_{i,t} + \beta^h_2 \widehat{S_{i,t}} + \gamma^{'h} X_{i,t} + \delta^h_{1j} \sum_{j=1}^{6} \epsilon^s_{i,t-j} + \delta^h_{2h} \sum_{h=1}^{hmax} \epsilon^s_{i,t+h} \\ + \delta^h_{3k} \sum_{k=0}^{5} (y_{i,t-k} - y_{i,t-k-1}) + \nu_{i,t+h}, \quad for \;\; h = 1, \ldots, 24 \end{aligned} \tag{5}$$

where $y_{i,t}$ is our proxy for bank loans in country i in month t. In our regressions, we distinguish between consumer loans ($y^C_{i,t}$) and housing loans ($y^H_{i,t}$). That is, $y_{i,t} \in (y^C_{i,t}, y^H_{i,t})$. $\epsilon^s_{i,t}$ are the residuals from equation 2, which serve as our measure of orthogonal sentiment shocks[5], while $\widehat{S_{i,t}}$ represents the sentiment driven by economic fundamentals. X is a vector of control variables that

[5]We do not include the shocks to present sentiment and future sentiment in the same regression owing to their high mutual correlation.

might influence bank lending[6] and α_i are country fixed effects, which enable us to control for time-invariant country-level factors that might influence bank lending. We also include three lags of both the dependent variable and our key explanatory variable ($\epsilon^s_{i,t}$) among the control variables. In line with Wiese et al. (2024), we include leads of sentiment shocks in equation 5 to address the bias caused by overlapping forecast horizons – $\delta^h_{2h} \sum_{h=1}^{hmax} \epsilon^s_{i,t+h}$ thus represents Teulings and Zubanov (2014) correction. The number of leads is equal to the length of the forecast horizon.

We estimate the equation 5 separately for each forecast horizon $h = 1, \ldots, 24$, and the estimated coefficients β^h_1 serve as point estimates of the impulse response of bank lending to pure sentiment shocks. The confidence intervals of the impulse response are obtained from the standard errors of the β^h_1 coefficients. We focus on pure sentiment shocks in our empirical strategy because these shocks are orthogonalized with respect to economic fundamentals, enabling a more straightforward identification of the effect of sentiment. Nevertheless, we control for new (fundamental-driven) sentiment ($\widehat{S_{i,t}}$) in all the regression specifications.

2.2.1 Role of Monetary Policy

The monetary policy stance is among the key determinants of bank lending, and the interaction between sentiment and monetary policy has been highlighted by Kashyap and Stein (2023). Therefore, in the following step of our empirical analysis, we study whether the monetary policy stance influences the effect of sentiment on bank lending. Specifically, when monetary policy is loose and credit is more abundant, sentiment could play a more important role as the determinant of bank lending. To identify the monetary policy stance, we follow the approach of Grimm et al. (2023): First, in line with Del Negro et al. (2019), we identify global and country-specific trends in interest rates and inflation using a VAR model with common trends. Next, we calculate the country-level natural interest rate ($r^*_{i,t}$) as the sum of the global and country-level trends in the short-term real interest rate ($r^*_{i,t} \equiv \bar{r}^w_t + \bar{r}^i_t$). Finally, we calculate the monetary policy stance as the 12-month moving average of the deviation of the actual short-term real rate from the natural rate:

$$stance_{i,t} = \frac{1}{36} \sum_{l=0}^{35} (r_{i,t-l} - r^*_{i,t-l}) \tag{6}$$

where $stance_{i,t}$ captures whether monetary policy has been tight or loose over the previous 36 months, while r represents the actual real short-term interest rate, which is calculated as the observed ex post real interest rate ($r_{i,t} = R_{i,t} - \pi_{i,t}$). Next, we explore whether the effect of consumer sentiment on bank lending is amplified when the monetary policy is loose or tight by estimating the following equation:[7]

$$\begin{aligned} y_{i,t+h} - y_{i,t} = \mathbb{I}_{i,t-1}(\alpha^{L,h}_i + \beta^{L,h}_{1e}\epsilon^s_{i,t} + \beta^{L,h}_2 \widehat{S_{i,t}} + \gamma^{L,'h} X_{i,t}) \\ +(1 - \mathbb{I}_{i,t-1})(\alpha^{T,h}_i + \beta^{T,h}_{1e}\epsilon^s_{i,t} + + \beta^{T,h}_2 \widehat{S_{i,t}} + \gamma^{T,'h} X_{i,t}) + \nu_{i,t+h}, \;\; for \;\; h = 1, \ldots, 24 \end{aligned} \tag{7}$$

where $\mathbb{I}_{i,t}$ is the indicator variable that takes a value of 1 when the monetary policy stance in the given country in the given month is loose ($stance_{i,t} < 0$) and 0 otherwise. Therefore, the coefficients $\beta^{L,h}_1$ enable us to generate impulse responses of bank lending to sentiment shocks when monetary policy is expansionary, whereas the coefficients $\beta^{T,h}_1$ represent the response of bank lending to sentiment shocks when monetary policy was tight during the previous 36 months.

[6] The control variables include the CBOE Volatility Index, spread between the yield of a 10-year government bond vis-a-vis Germany, the 3-month interbank interest rate, the exchange rate of domestic currency against the Euro (U.S. dollar in the case of euro area members), the inflation rate, the industrial production index as a proxy for monthly real economy developments, Euro Area shadow rate, an index for changes in macroprudential policy, and quarterly seasonal dummies.

[7] To keep the notation of equation 7 parsimonious, we include the leads and lags of pure sentiment, as well as the lags of the dependent variable in the vector of control variables X.

3 Results

3.1 Stylized Facts

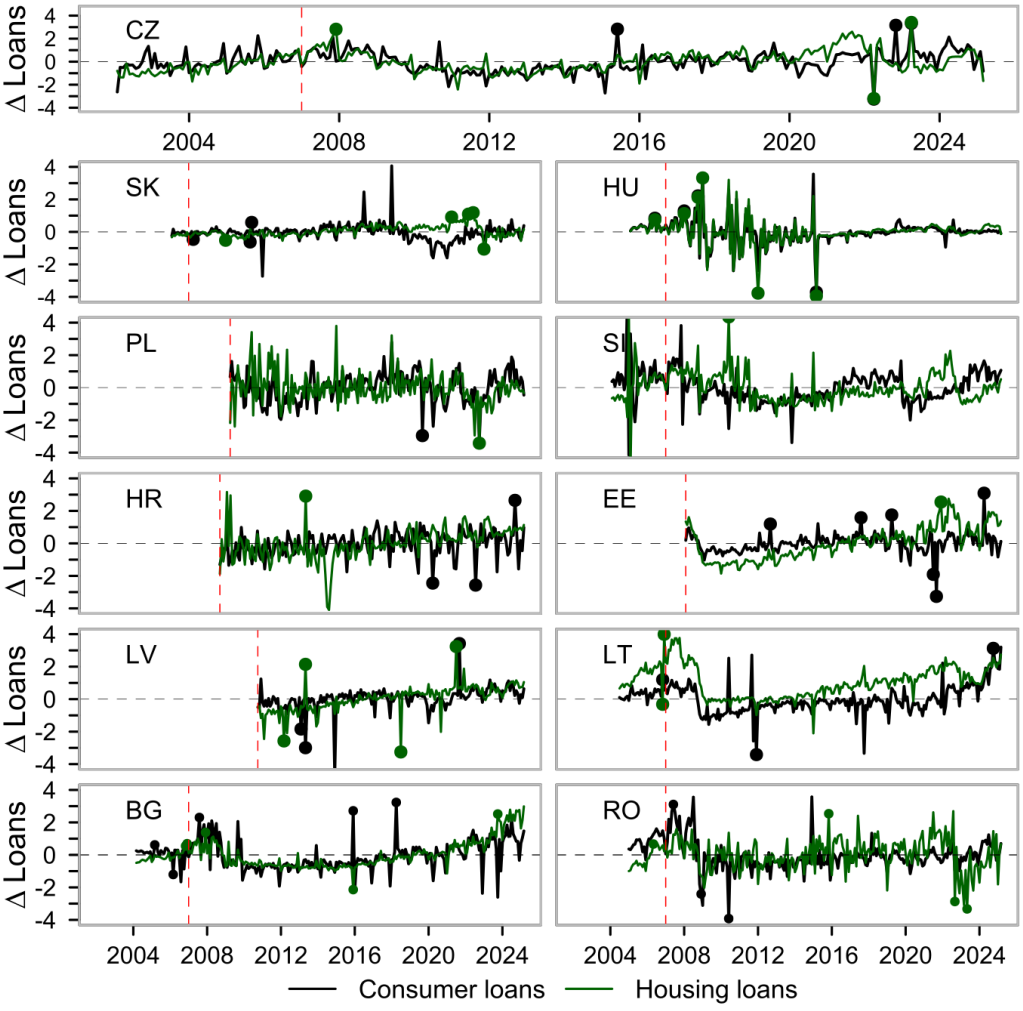
Before presenting our main results, we first provide some stylized facts and establish key properties of our main variables of interest, i.e., housing and consumer loan developments, along with decomposed news-based sentiment and pure sentiment indicators.

3.1.1 Household and Consumer Loans: Heterogeneous Dynamics

The visualization of loan changes (see Figure 1) allows us to observe that fluctuations in the credit market have generally decreased, with periods of increasing fluctuations around the Global Financial Crisis, after the pandemic period, and in the subsequent high-inflation, high-interest rate period. The dots in Figure 1 refer to points that were winsorized as they surpassed their 3.5 $\times$ standard deviation distance from the historical (up to that point) mean. These points appear mostly during such stressful periods. We can see several known credit market-specific events. For example, in Slovakia, housing and consumer loans show very different dynamics, particularly after 2016, which can be attributed to reduced interest rates and the 'lex Beblavy' (Košťálová et al., 2022) that simplified the refinancing of existing loans and subsequently caused a shock in consumer credit growth. In Hungary, the 2015 reform eliminated foreign exchange loans, which helped stabilize bank lending. In fact, using the Inclan and Tiao (1994) algorithm with the Sansó et al. (2004) test, one can identify a volatility break in the series in February 2015.

The results in Table 1 reveal several stylized facts about loans: i) housing loans do not show severe persistence, ii) they tend to be seasonal, and iii) they are subject to sudden shocks (see kurtosis). Given the slow-pace nature of the economic environment, lower persistence and especially not that uncommon shocks ('spikes') in credit changes might, at least to some extent, be driven by other than rationally expected changes in fundamentals of the underlying economy.

Figure 1: Monthly Changes in Consumer and Housing Loans



Notes: To improve comparability across countries, changes in loans are Z score standardized in this figure. Dots correspond to the smoothed observations, and the dashed vertical red line represents the point at which the panel model analysis begins.

Table 1: Characteristics of Key Variables of Interest: Credit Expansion and Consumer Sentiment

	Mean	SD	Skew.	Kurt.	Min	Q1	Q2	Q3	Max	$\rho(1)$	$\rho(12)$	EL
Panel A: Slovakia												
Consumer Loans	24.63	81.83	9.4	117.1	-198.8	4.66	22.74	37.11	1075.76	0.05	0.08	***
Housing Loans	161.41	262.78	-12.5	176.6	-3584.28	112.74	166.19	226.64	491.4	0.13	0.02	***
Panel B: Czech Republic												
Δ Consumer Loans	1107.9	1343.4	1.2	7.9	-4282.2	306.4	960.9	1879.0	9747.0	0.32	0.28	***
Δ Housing Loans	6352.1	3794.6	0.4	5.8	-15046.9	3942.93	5980.9	8527.91	24535.2	0.51	0.28	***
Panel C: Hungary												
Consumer Loans	16509	168170.9	-2.7	38.6	-1601383	-21579	20882	61559	943454	0.11	0.13	
Housing Loans	31300	241856	-2.9	30.2	-2151252	-18471.33	41609	97756.43	1079083	0.17	0.11	*
Panel D: Poland												
Consumer Loans	444.7	967.8	-1.4	7.5	-5662.0	-115.8	545.5	1013.0	3154.0	0.40	0.22	***
Δ Housing Loans	1396.3	4289.7	0.4	2.9	-15504.0	-940.3	1074.0	3399.8	17683.0	0.06	0.08	
Panel E: Slovenia												
Consumer Loans	31.55	34.34	1.0	8.0	-145.93	10.58	24.79	50.12	239.33	0.29	0.19	***
Housing Loans	7.65	27.43	0.5	4.7	-106.1	-10.24	6.23	24.46	157.1	0.33	0.31	***
Panel F: Croatia												
Consumer Loans	24.13	80.93	-0.1	4.5	-307.0	-12.0	30.0	66.0	385	0.41	0.24	***
Housing Loans	-6.95	22.27	2.7	26.3	-91.0	-18.0	-6.0	4.0	177	0.11	0.33	***
Panel G: Estonia												
Consumer Loans	32.11	33.46	0.4	-0.5	-30.0	4.0	30.0	55.5	124	0.90	0.64	***
Housing Loans	0.05	15.6	-2.5	47.9	-147.0	-5.0	0.0	5.0	108	0.10	0.06	**
Panel H: Latvia												
Consumer Loans	-8.79	38.85	-2.5	16.6	-279.0	-26.0	-3.0	10.8	126	0.33	0.24	***
Housing Loans	-0.7	16.65	-4.9	43.9	-154.0	-4.0	1.0	5.0	69	0.14	0.20	***
Panel I: Lithuania												
Consumer Loans	51.57	49.94	0.5	0.8	-105.0	7.0	49.0	87.0	256	0.79	0.56	***
Housing Loans	8.25	26.47	-0.6	11.9	-179.0	-4.0	5.0	21.0	121	0.44	0.28	***
Panel J: Bulgaria												
Consumer Loans	53.73	77.54	-1.0	17.3	-572.29	7.01	37.35	80.24	376.06	0.67	0.50	***
Housing Loans	38.07	63.74	1.9	10.9	-128.1	-2.01	30.65	64.6	493.13	0.28	0.17	***
Panel K: Romania												
Consumer Loans	90.85	75.84	-0.6	2.4	-274.57	46.11	97.75	142.35	300.86	0.30	0.11	***
Housing Loans	54	257.33	-0.3	8.5	-1575.49	-59.14	18.22	147.33	1104.37	0.55	0.36	***

Notes: The first, second and third quartiles are denoted as Q1, Q2 and Q3, respectively. $\rho(.)$ denotes the value of the auto-correlation coefficient at the given order. The EL column shows the significance of the Escanciano and Lobato (2009) serial-correlation test, where the maximum lag order was set to 12. All variables were tested for the presence of a unit-root using the test of Sul et al. (2005), the long-run variance adjusted test of KPSS (1992) with an intercept and Quadratic spectral weighting scheme used to estimate the long-run variance. At the 10%, the null of no-unit root was not rejected for any of the variables. Δ denotes the first differences.

The data also show that loan dynamics vary across countries not only in terms of co-movement between consumer and housing loans but also in terms of persistence, implying different shock absorption behaviours. A common feature among loans is that their dynamics are frequently affected by shocks in both directions. Generally, changes in housing and consumer loans show a small level of co-movement, with a Pearson correlation coefficient of 0.18 being the median and 0.25 the average across the 11 countries. Only Hungary has a much larger co-movement of 0.95, followed by the Czech Republic with a value of 0.50, while Slovenia presents the lowest at -0.11. These results motivate our decision to model consumer and housing loans separately.

3.1.2 Sentiment Indices: News-driven Sentiment and Pure Sentiment

We decompose sentiment indices (present and future) into news-driven and pure sentiment (see Eq. 2), where news-driven sentiment is approximated by an average forecast from the four models. Before using pure sentiment, or shocks, in local projections, we evaluate the accuracy of our estimates (forecasts) of news-driven sentiment in the following table 2. In the first column, we show the mean square error from the naive random-walk model. The values in the remaining columns show percentage improvements (a positive number) in forecast accuracy compared with the random-walk models. For example, the value of -10.1 in Panel A for the row 'Future sentiment' means that the Elastic Net (EN) model underperforms the random walk by 10.1% in terms of the mean square error. The naive random walk model of sentiment is difficult to beat (see negative numbers in Table 2), which can be partly explained by the fact that sentiment shows high persistence (see Appendix B1) and that it probably already reflects most economic fundamentals. However, a combination forecast (column CF) consistently outperforms the naive model in all 22 cases, with forecast improvements ranging from 2.3% for present sentiment in Croatia (Panel F) to 27.3% for future sentiment in Slovakia (Panel A) and average and median improvements of 13.2% and 14.4%, respectively. One exception is represented by future sentiment in Lithuania, where even the trimmed average underperforms the random walk by -7.8%. Given that the preferred model is not known in advance, we opt for the combination forecasts, which generally result in more accurate sentiment predictions.

News-driven sentiment tracks the actual sentiment index closely (see small MSE in Table 2 and Figure 2) and, as expected, displays a high level of persistence; up to 0.97 for news-driven future sentiment for Lithuania and Slovakia and up to 0.94 for Slovakia present sentiment in Poland to 0.98 for news-driven present sentiment in Slovakia. Across all 22 estimated pure sentiment time series that represent our proxy for exogenous shocks, in only two instances, shocks still show a mild presence of significant serial-correlation at the 5% level (see rows 'Pure' in Table B1). Generally, the pure sentiment is noisier and subject to large spikes. These spikes are clustered in the Global Financial Crisis and COVID-19 periods, which is expected as these were periods with considerable exogenously driven uncertainty.

Next, we identify news-based sentiment by using the combination forecasts (CF) in Equation 2. Trends in news-driven sentiment and pure sentiment are shown in Figure 2, while their descriptive statistics are reported in Appendix B1. News-driven sentiment closely tracks the actual sentiment index (see small MSE in Table 2 and Figure 2) and, as expected, displays a high level of persistence, reaching 0.97 for news-driven future sentiment for Lithuania and Slovakia, 0.94 for present sentiment in Poland and Slovakia, and 0.98 for news-driven present sentiment in Slovakia.

Across all 22 estimated pure sentiment time series that represent our proxy for exogenous shocks, shocks still show a mild presence of significant serial correlation at the 5% level in only two instances (see the 'Pure' rows in Table B1). Generally, pure sentiment is noisier and subject to large spikes. These spikes are clustered in the Global Financial Crisis and COVID-19 periods, which is expected, as these were periods with considerable exogenously driven uncertainty.

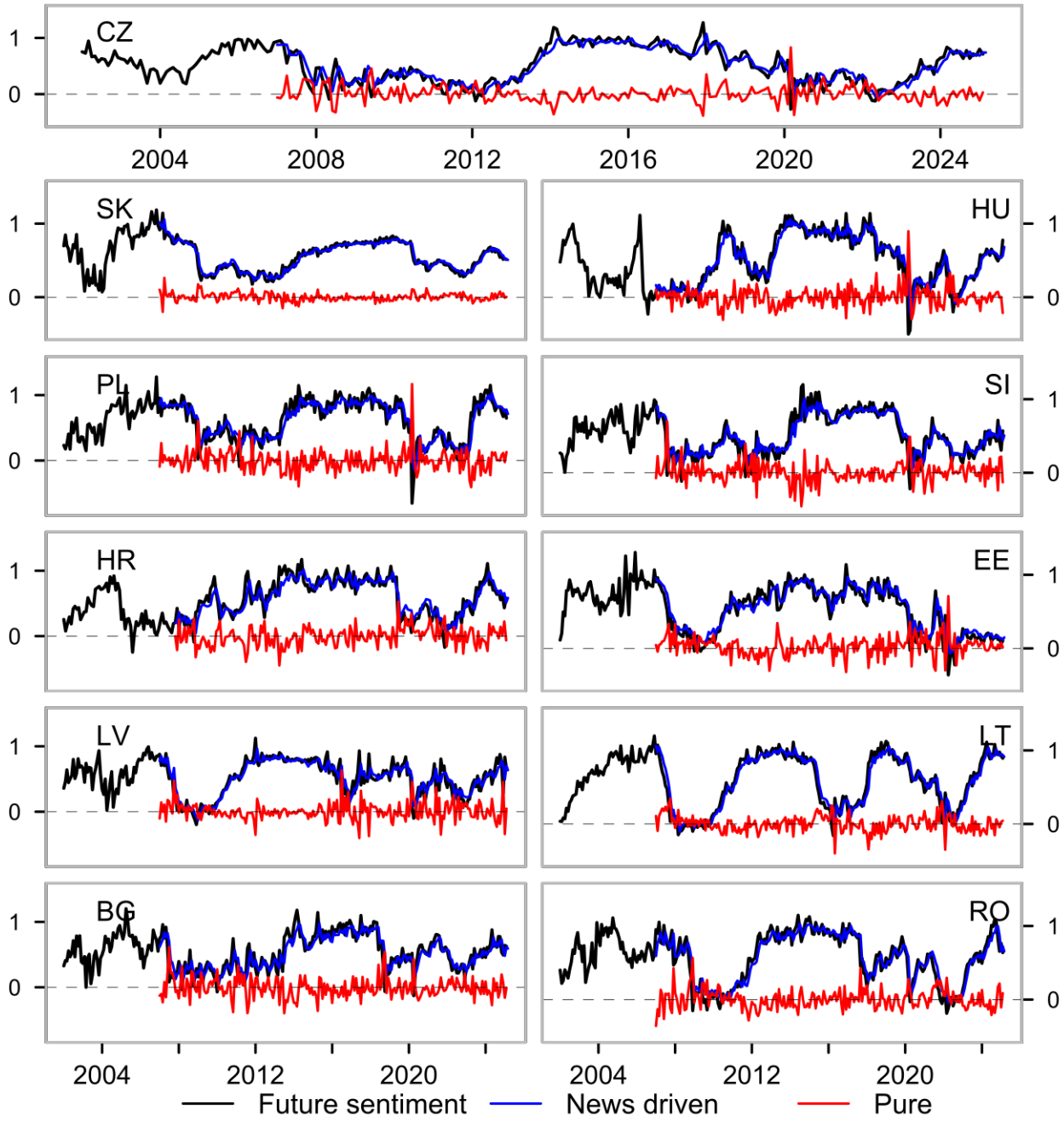
In summary, similarly to loan dynamics, sentiment seems to behave distinctively across the eleven countries and the two sentiment categories (future and present). News-driven sentiment

Table 2: Consumer Sentiment Mean Square Forecast Errors

	RW	EN	RF	XGB	CF
Panel A: Slovakia					
Future sentiment	0.004	-10.1	1.4	-8.9	27.3
Present sentiment	0.006	-7.3	-21.8	-20.3	7.9
Panel B: Czechia					
Future sentiment	0.023	-11.4	3.1	-4.7	7.6
Present sentiment	0.043	-1.3	21.0	4.0	9.5
Panel C: Hungary					
Future sentiment	0.022	-19.3	-4.6	-0.5	21.3
Present sentiment	0.122	6.2	21.3	2.9	18.4
Panel D: Poland					
Future sentiment	0.033	-1.7	8.8	4.3	16.5
Present sentiment	0.085	-23.8	27.7	13.0	12.7
Panel E: Slovenia					
Future sentiment	0.023	-4.5	4.3	2.0	14.5
Present sentiment	0.052	-5.1	16.3	19.0	14.3
Panel F: Croatia					
Future sentiment	0.025	-4.4	6.2	2.8	11.2
Present sentiment	0.036	-3.8	3.4	-5.8	2.3
Panel G: Estonia					
Future sentiment	0.021	-1.1	2.8	3.5	14.8
Present sentiment	0.103	17.5	28.5	19.7	16.7
Panel H: Latvia					
Future sentiment	0.024	8.2	17.6	18.2	21.1
Present sentiment	0.058	4.9	20.9	18.9	14.8
Panel I: Lithuania					
Future sentiment	0.011	-15.7	-53.1	-35.7	-7.8
Present sentiment	0.041	-3.6	13.6	3.9	8.8
Panel J: Bulgaria					
Future sentiment	0.033	-1.7	8.8	4.3	16.5
Present sentiment	0.085	-23.8	27.7	13.0	12.7
Panel K: Romania					
Future sentiment	0.033	-1.7	8.8	4.3	16.5
Present sentiment	0.085	-23.8	27.7	13.0	12.7

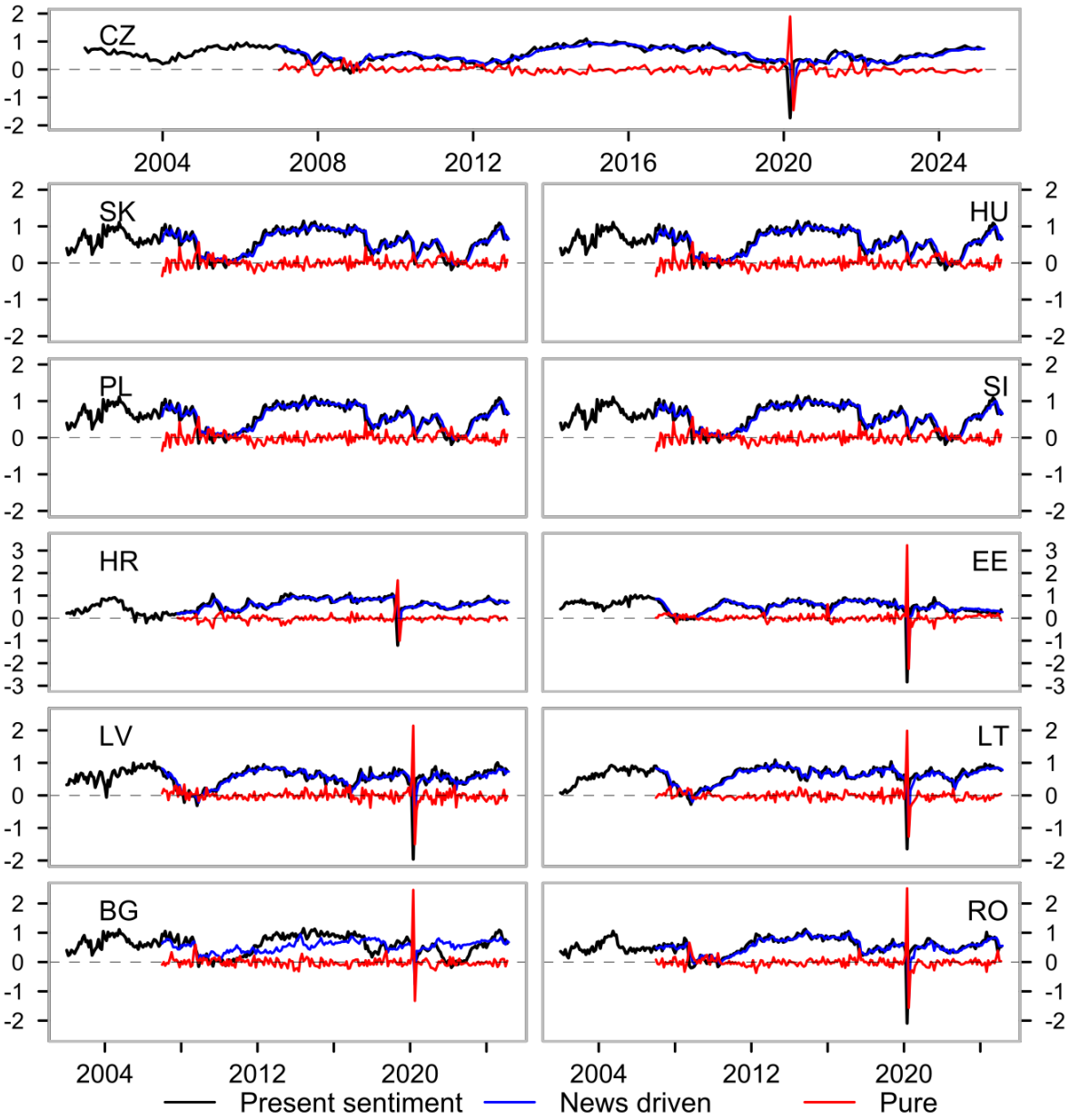
Notes: The RW column denotes the mean square error of the random-walk model – our benchmark – and remaining columns show percentage improvements (positive values) or deterioration (negative values) in forecasting accuracy for models: Random Walk (RW), Elastic Net (EN), Random forest (RF) and Boosted regression tree (XGB). The CF column is the combination forecast, a trimmed average removing the highest and lowest forecast values. The decomposition of sentiment is based on the combination forecasts.

Figure 2: Future sentiment decomposition



changes slowly, whereas pure sentiment is much noisier, less persistent, and prone to sudden changes that cluster in uncertain times, which suggests that our identification strategy leads to meaningful estimates of exogenous shocks. In the next section, we apply the local projection framework of Jorda (2005) to formally explore the effect of such shocks to consumer sentiment on consumer and housing loans.

Figure 3: Present sentiment decomposition



3.2 Consumer Sentiment and Bank Loans

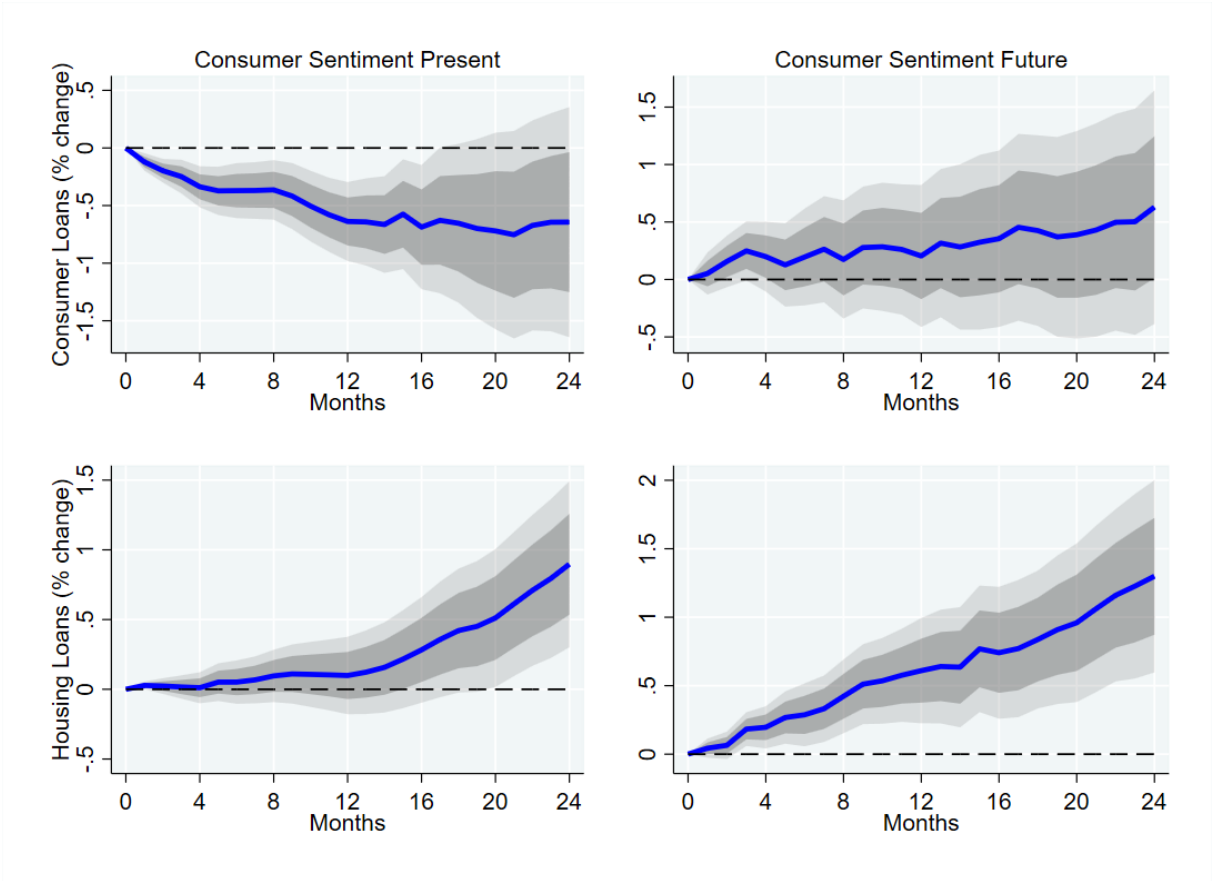
In the following subsection, we outline our findings of the causal effect of consumer sentiment on bank lending. The results of the baseline regressions are reported in Figure 4.

The results exhibit some notable heterogeneity, as the observed relationships vary depending on the type of loan (consumer vs. housing) and sentiment shock (present vs. future). In general, we find that sentiment shocks have a less positive effect on consumer loans than on housing loans and that shocks to future sentiment have a more positive effect than shocks to present sentiment do. To some extent, this heterogeneity in results supports our approach of studying consumer and housing loans separately and distinguishing present and future sentiment.

Specifically, shocks to present sentiment have a negative effect on consumer loans, and the effect is statistically significant (top left panel of Figure 4) for up to 16 months after the shock. An

increase in consumer sentiment about present economic conditions of a magnitude that corresponds to a 1 out of 20 event (i.e., 95^{th} percentile, or three months in five years) is followed by a reduction in consumer loans of approximately 0.6% 16 months after the shock. In contrast, shocks to future sentiment have a consistently positive effect on consumer loans, but the estimated effect shows greater uncertainty (top right panel of Figure 4) and is not significant.

Figure 4: Effect of Pure Sentiment Shocks on Bank Lending



Notes: Cumulative IRFs of bank lending to pure sentiment shocks. The magnitude of the sentiment shock is standardized so that it represents a 1 in 20 (95^{th} percentile) increase in the respective sentiment measure. The top panel displays the responses of consumer loans, while the bottom panel shows the responses of housing loans. The left panel displays the responses to shocks to present sentiment, while the right panel displays the responses to shocks to future sentiment. The solid line represents the point estimate, and the shaded areas correspond to the 68% and 90% confidence intervals. The point estimates are based on the coefficients β_1^h from equation 5 over the entire forecast horizon $h = 1, \ldots, 24$. Month 1 ($h = 1$) is the first month after the sentiment shock. Driscoll–Kraay standard errors are used to calculate the confidence bands. Y-axis: deviation in percentage points. X-axis: time in months.

The bottom panels of Figure 4 depict the responses of housing loans to sentiment shocks. For housing loans, the effect of sentiment shocks appears to be greater: Positive sentiment leads to a persistent and statistically significant increase in housing loans. Shocks related to the sentiment about future economic conditions have a more positive effect on housing loans than shocks to sentiment about the present: A 1 in 20 (95^{nd} percentile) increase in present and future sentiment leads to a cumulative increase in housing loans over a 24-month period of approximately 0.90% and 1.2%, respectively. As housing loans in our panel of CEE economies increase, on average, by some 14% over a 24-month period, a large positive shock to sentiment about the future can increase the rate of growth of housing loans by approximately one-tenth, a change that is relevant to policymakers.

To conclude, our results indicate that sentiment shocks have a more pronounced effect on

housing loans than on consumer loans, with future sentiment playing a more consistent positive role for housing loans. Our main results imply that it is important to properly distinguish between present and future sentiment about economic conditions. Specifically, consumers might base their expectations of future developments on current economic conditions, leading to a high degree of correlation between present and future sentiment. In fact, even our orthogonalized measures of present and future pure sentiment shocks exhibit a moderate level of correlation (0.39), which highlights the importance of properly distinguishing between present and future sentiment.

Therefore, to ensure that our findings on the greater effect of future sentiment are robust, we eliminate the common component of present and future sentiment by taking the difference between the two sentiment measures ($\epsilon_{i,t}^{s,\mathrm{F}} - \epsilon_{i,t}^{s,\mathrm{P}}$) and using this difference as an alternative measure of sentiment about the future – relative future sentiment. A positive value of relative future sentiment indicates that consumers are more positive about the future than about the present. After re-estimating our baseline models with relative future sentiment, we find that the greater the discrepancy between the current and future economic outlooks is, the greater the positive effect on not only housing loans but also, in this setup, consumer loans (see Figure 5). These results corroborate our finding that sentiment about the future has a stronger (and more positive) effect on bank lending in Central and Eastern Europe than sentiment about the present.

Our finding that positive sentiment increases bank lending indicates that as economic agents become more optimistic, they become less risk averse and increase their loan demand. Our results are in line with the findings of Constantinides et al. (2025), who reported that positive sentiment temporarily increases economic growth. While Constantinides et al. (2025) identify one channel through which sentiment influences economic growth (i.e., by lowering the local cost of equity), our results indicate that sentiment can influence the real economy through another channel, the bank lending channel.

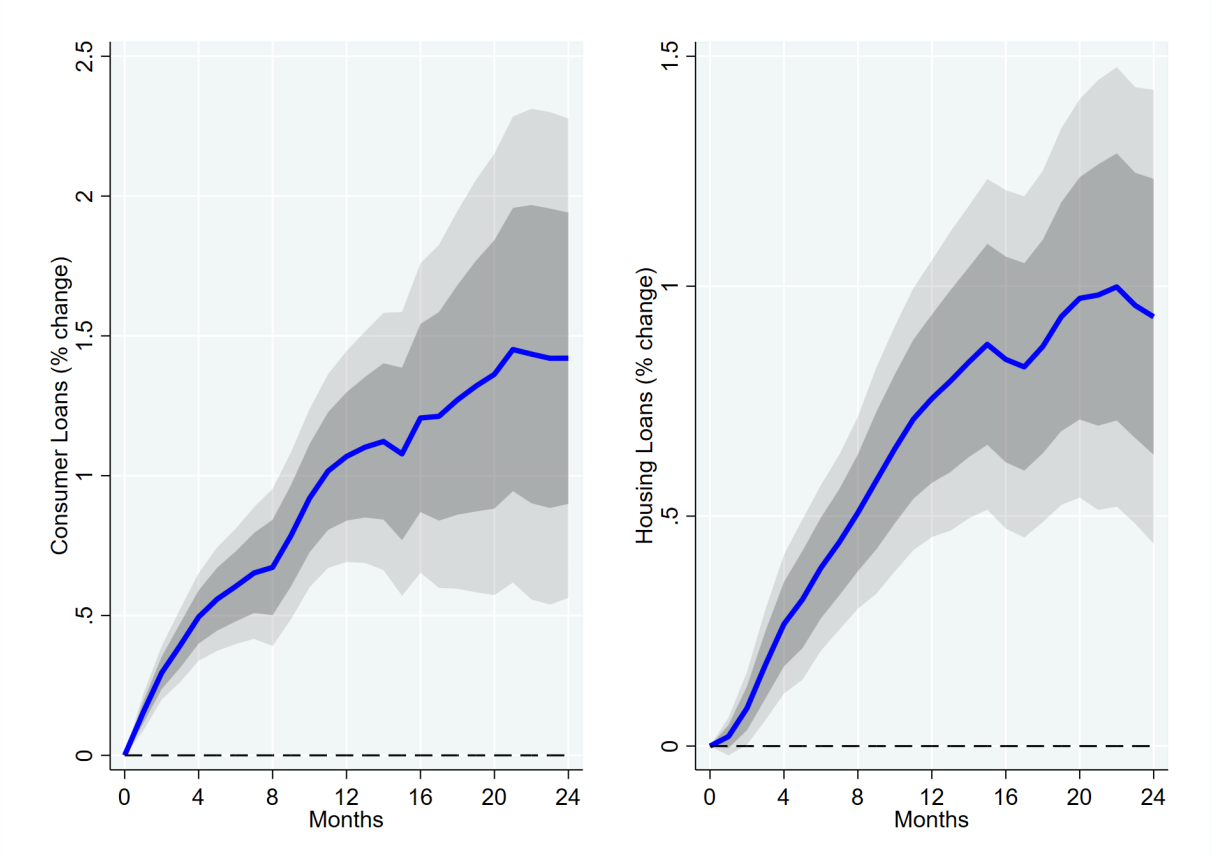
Furthermore, we find that compared with consumer loans, housing loans respond to sentiment shocks more positively. Two potential interpretations underline this channel. First, housing loans are generally larger and have a longer maturity. Therefore, consumers are likely to be more cautious when deciding on their demand for housing loans, and positive sentiment (particularly about the future) thus plays an important role in influencing decisions regarding the housing loan demand. Second, positive sentiment might lead to higher asset prices, including house prices (Khan et al., 2019), which then increases the demand for housing loans (Soo, 2018).

Interestingly, we also find that consumer loans fall following a positive shock to present sentiment. These findings indicate that as households become more optimistic about the current state of the economy, they reduce their demand for expensive and short-term consumer loans, as they may feel that they no longer require consumer loans to smooth consumption. Instead, as precautionary savings are likely to decrease during more stable (perceived) economic conditions (Mody et al., 2012), households might opt to fund their current consumption with savings. Conversely, when households' sentiment becomes more negative, households start to demand more consumer loans, as they perceive the need to smooth their consumption during more challenging times. Finally, more positive sentiment about the future does not appear to affect consumer loans. Since consumer loans are rather short term, the expectations of households about the future do not appear to be relevant for their decisions regarding consumer loan demand.

3.3 State-Dependent Effect of Sentiment

The data in Figures 1- 2 suggest that sentiment was elevated in the aftermath of the Global Financial Crisis and shortly before the pandemic, as were housing and consumer loans, especially in the late 2010s. Similar co-movement is observed after the pandemic. Considering the importance of monetary policy as the determinant of bank lending and the interaction between monetary policy and sentiment that has already been highlighted by the empirical literature (Kashyap and Stein, 2023), we explore whether the monetary policy stance might drive our results. In particular, given

Figure 5: Effect of Relative Future Sentiment Shocks on Bank Lending



Notes: Cumulative IRFs of bank lending to pure sentiment shocks. The magnitude of the sentiment shock is standardized so that it represents a 1 in 20 (95^{th} percentile) increase in the sentiment measure. The IRFs are the responses to shocks to *relative* future sentiment, which is calculated as the difference between the sentiment about the future and the sentiment about the present. The left panel displays the responses of consumer loans, while the right panel shows the responses of housing loans. The solid line represents the point estimate, and the shaded areas correspond to 68% and 90% confidence intervals. The point estimates are based on the coefficients β_1^h from equation 5 over the entire forecast horizon $h = 1, \ldots, 24$. Month 1 ($h = 1$) is the first month after the sentiment shock. Driscoll–Kraay standard errors are used to calculate the confidence bands. Y-axis: deviation in percentage points. X-axis: time in months.

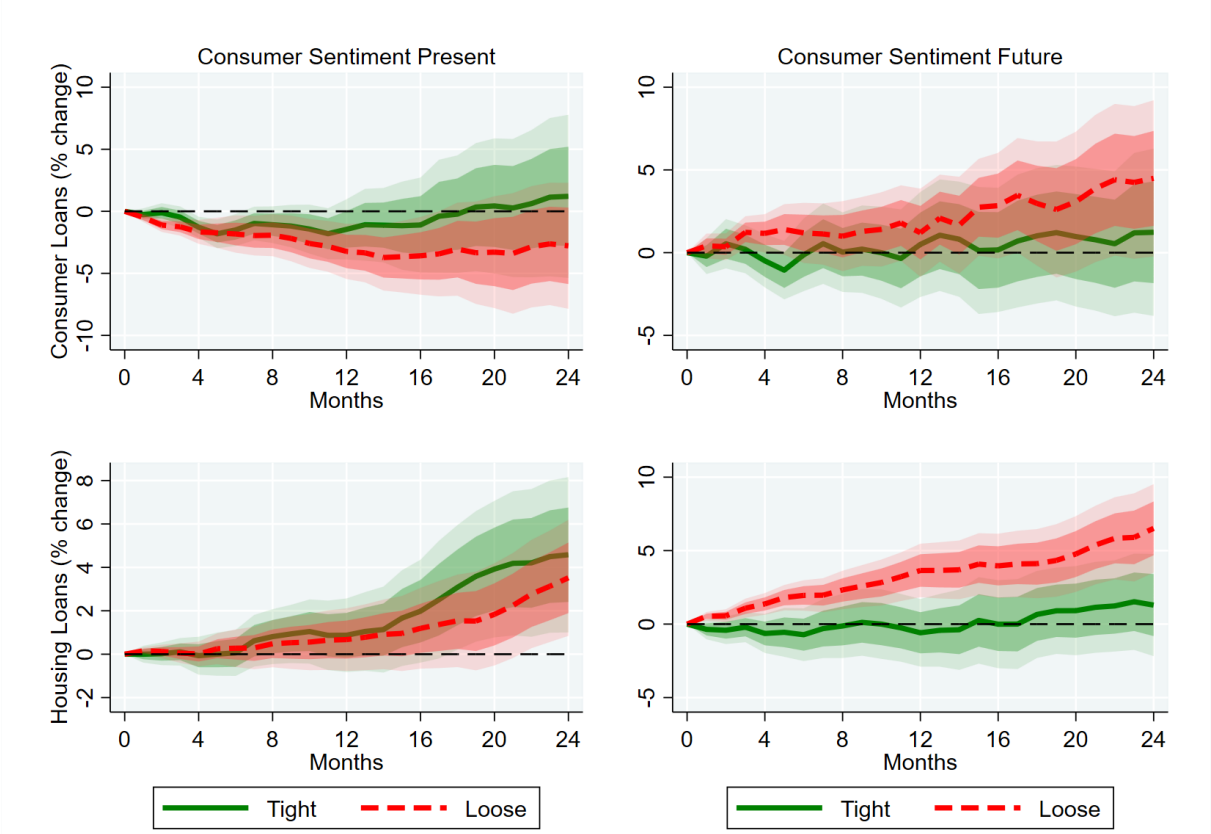
the co-movement observed between lending and sentiment, the highlighted period could be characterized as a period of loose monetary policy. In the next step of our analysis, we explore whether the effect of sentiment on bank lending is state dependent, or monetary policy dependent.

Figure 6 shows the impulse responses of bank lending to pure sentiment shocks when the monetary policy stance was persistently tight or persistently loose during the previous 36 months. Positive future sentiment shocks seem to have a positive effect on bank loans only when the monetary policy stance is persistently loose. This positive effect can be observed for both consumer loans and housing loans, with the effect being greater in magnitude for housing loans. Conversely, when the monetary policy stance is persistently tight, the effect of future sentiment shocks disappears:[8] Thus, an improvement in sentiment about the future affects neither consumer nor housing loans. Similarly, the negative effect of present sentiment on consumer loans also appears to be driven by

[8]The vector of control variables includes the short-term interest rate. Thus, the impulse responses in Figure 6 should not be driven by the effect of the monetary policy stance itself on bank lending but should instead reflect heterogeneous responses of bank lending to sentiment shocks under different monetary policy stances.

periods with loose monetary policy.

Figure 6: Effect of Pure Sentiment Shocks on Bank Lending – The Role of Monetary Policy Stance



Notes: Cumulative IRFs of bank lending to pure sentiment shocks. The magnitude of the sentiment shock is standardized so that it represents a 1 in 20 (95^{th} percentile) increase in the respective sentiment measure. The solid (dashed) lines represent the responses of bank lending to sentiment when the monetary policy stance is tight (loose). The top panel displays the responses of consumer loans, while the bottom panel shows the responses of housing loans. The left panel displays the responses to shocks to present sentiment, while the right panel displays the responses to shocks to future sentiment. The solid (dashed) line represents the point estimate, and the shaded areas correspond to 68% and 90% confidence intervals. The point estimates are based on the coefficients β_{1r}^h and β_{1e}^h from equation 7 over the entire forecast horizon $h = 1, \ldots, 24$. Month 1 ($h = 1$) is the first month after the sentiment shock. Driscoll–Kraay standard errors are used to calculate the confidence bands. Y-axis: deviation in percentage points. X-axis: time in months.

We interpret the finding that tighter monetary policy limits the transmission of sentiment shocks to bank lending as follows: While positive sentiment is associated with more risk-taking (Cubillas et al., 2021), tighter monetary policy has been shown to constrain risk-taking behaviour (Bauer et al., 2023; Kashyap and Stein, 2023). Thus, an increase in sentiment that occurs during periods with comparatively tight monetary policy can have a limited effect on bank lending, since higher sentiment does not lead to more actual risk-taking. Conversely, when the monetary policy stance is loose, a positive sentiment shock coupled with more risk-taking behaviour might lead to increased loan demand. Similarly, when monetary policy is expansionary and liquidity is abundant, banks are also more likely to meet the growing loan demand with an expansion of loan supply, as banks are less risk averse and "searching for yield" (Altunbas et al., 2014; Rajan, 2005). These results thus imply that a loose monetary policy comes with an additional risk factor associated with (irrational) sentiment and induces overlending.

3.4 Sentiment, Lending and Financial Stability: The Effect on Bank Leverage

The above results suggest that at least part of the increase in lending (housing loans) can be attributed to (positive) shocks to sentiment with respect to current/past or future economic conditions. Such shocks to lending are not driven by improvements in macroeconomic fundamentals and might affect financial stability, particularly that of banking institutions. To test this hypothesis, we replace bank lending as our response variable with a measure of banks' financial stability. Following Uppal (2025), we use country-level bank leverage, defined as the ratio of total assets to capital, which serves as a proxy for the financial stability of the banking system. The impulse responses of bank leverage to positive sentiment shocks, reported in Figure 7, suggest that the channel from sentiment shocks to bank lending and then to increased bank leverage is plausible. An overly positive shock to consumer sentiment could make the banking system less safe, since bank leverage increases after positive shocks to present sentiment and to future sentiment, with the increase being greater for future sentiment. The increase in bank leverage is not only statistically significant but also quite persistent , with bank leverage remaining elevated even 24 months after the shock. These findings highlight the potential negative implications of overly positive sentiment for financial stability.

3.5 Robustness Checks

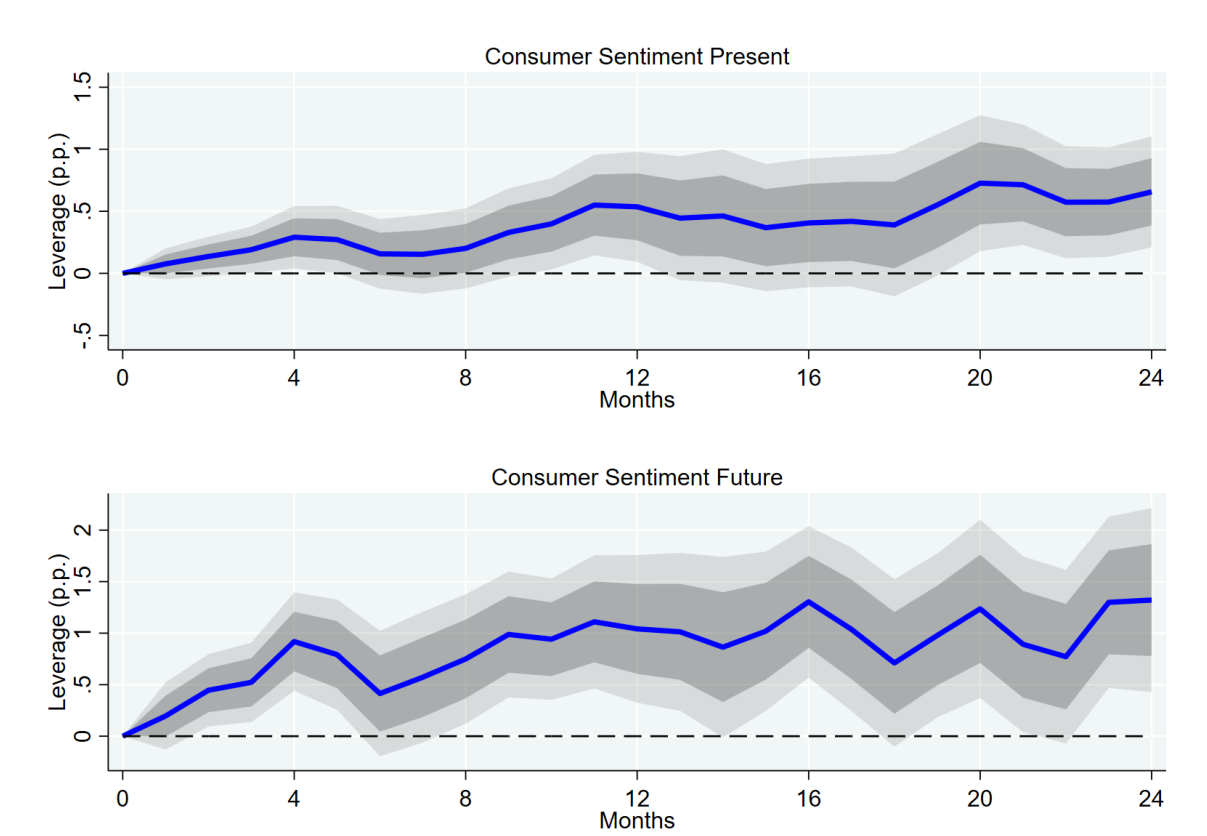
We conduct several robustness checks to verify the robustness of the findings on the effect of sentiment on bank lending. First, we examine whether the number of lags of the dependent variable (k in equation 5) and the number of lags of the sentiment shocks (j in equation 5) influence our main conclusions. Therefore, we rerun all the baseline regressions, increasing the number of lags from 6 to 9 and then to 12. We report the results with 9 lags and 12 lags in Figure C1 in the Appendix. Overall, the impulse responses are in line with our baseline regressions – with the exception of the positive effect of consumer present sentiment on housing loans. Although this impulse response eventually turned positive in the baseline regressions, it lost statistical significance with the use of a greater number of lags. Therefore, we take the findings on the positive effect of present sentiment on housing loans with a grain of salt. Nevertheless, this robustness check confirms our initial conclusion that future sentiment has a more positive effect on loans than present sentiment does.

In the next set of robustness checks, we address the possibility that our results could be driven by a particular period. We run robustness checks in which we i) drop the period of the Global Financial Crisis of 2008–2009 and ii) the initial period of the COVID-19 pandemic (2020) since both of these periods were marked by substantial macroeconomic fluctuations. We report the results of these robustness checks in Figure C2. Although the exclusion of these crisis periods leads to a small decrease in the magnitude of the estimated effect, our main conclusions remain unaffected: Consumer loans fall following a positive shock to present sentiment, and housing loans increase following a positive shock to future sentiment. The observed decrease in the magnitude of the estimated effect indicates that irrational sentiment has a more pronounced effect during periods of large macroeconomic fluctuations, but our conclusions do not solely hinge on these uncertain periods.

In the final set of robustness checks, we sharpen inference by using a bootstrap for the standard errors on regression coefficients. First, we use a simple parametric bootstrap clustered at the country level.[9] Second, since our panel contains only a small number of countries (clusters), which

[9] In the baseline regressions, owing to our relatively long time series, we have opted to use Driscoll–Kraay standard errors, which are robust to autocorrelation, heteroscedasticity, and cross-sectional dependence. However, we do not cluster standard errors at the country level. To account for the potential within-country correlation of errors, we cluster standard errors at the country level in this robustness check.

Figure 7: Effect of Pure Sentiment Shocks on Bank Leverage



Notes: Cumulative IRFs of bank leverage to pure sentiment shocks. The magnitude of the sentiment shock is standardized so that it represents a 1 in 20 (95^{th} percentile) increase in the respective sentiment measure. The upper panel displays the bank leverage response to the shock to present sentiment, whereas the lower panel displays the bank leverage response to the shock to future sentiment. The solid line represents the point estimate, and the shaded areas correspond to 68% and 90% confidence intervals. The point estimates are based on the coefficients β_1^h from equation 5 over the entire forecast horizon $h = 1, \ldots, 24$. Month 1 ($h = 1$) is the first month after the sentiment shock. Driscoll–Kraay standard errors are used to calculate the confidence bands. Y-axis: deviation in percentage points. X-axis: time in months.

precludes the use of conventional inference methods (Cameron et al., 2008; Gric et al., 2022), we also apply the wild cluster bootstrap of Roodman et al. (2019). The results are reported in Figure C3 in the Appendix. Even though confidence intervals become wider with bootstrapping, the negative response of consumer loans to an increase in present sentiment and the positive response of housing loans to an improvement in future sentiment remain statistically significant.

4 Conclusion

In this study, we analyse the effect of consumer sentiment on bank lending for the period from January 2008 until March 2025 using a sample of 11 Central and Eastern European economies that have experienced significant credit expansion over the past two decades. To identify the effect of sentiment, we use a combination of several machine learning techniques. As our measure of sentiment, we use a consumer sentiment index derived from a survey of consumers, which is decomposed into i) the component driven by economic fundamentals (fundamental-driven or news-based) and ii) the sentiment component that is orthogonal to economic fundamentals, or

pure sentiment. The decomposition is carried out using an ensemble of penalized linear regression models (elastic net), random forest, boosted regression tree, and a naive random walk model. The estimated pure sentiment serves as a proxy for sentiment shocks, which we use to estimate the impulse responses of bank lending to these shocks via local projections.

In addition to providing a novel identification strategy, we contribute to the literature by distinguishing between the sentiment associated with present/past economic conditions and the sentiment about future economic conditions. We find that an increase in sentiment above what is expected on the basis of macroeconomic fundamentals leads to an increase in housing loans, while it has only a limited effect on consumer loans. Shocks to future sentiment have a stronger effect on bank lending than shocks to present/past sentiment do. The effect is nontrivial and can account for approximately one-tenth of the changes in loans. Although we find these effects to be robust to some modelling choices, or even when we exclude the Global Financial Crisis and COVID-19 periods, we find that they are relevant only during a period of persistent loose monetary policy.

Our results also extend the literature on the real economic effects of sentiment by identifying another channel through which sentiment might influence the real economy: the bank lending channel. When consumer sentiment is high, consumers might become more optimistic and less risk averse and thus more willing to make major long-term investments, leading to higher demand for housing loans. Nevertheless, the demand for consumer loans, which are typically smaller in magnitude and have shorter maturities than housing loans, does not seem to increase after a positive sentiment shock. Presumably, as consumers become more optimistic, they do not feel the need to increase their demand for (expensive) consumer loans to facilitate consumption smoothing. Instead, they might opt to finance their consumption from savings or expected higher earnings in the near future. Finally, we also show that positive shocks to sentiment might not only amplify loan growth but also increase the vulnerability of the banking system by increasing bank leverage, thereby contributing to worsening financial stability.

Our results have several policy implications. Previous research has already shown that monetary policy operates through the risk-taking channel (Bauer et al., 2023; Kashyap and Stein, 2023). We find evidence that positive sentiment stimulates bank lending only when persistently loose monetary policy creates favourable conditions, potentially by making liquidity abundant and by encouraging risk-taking, especially if such sentiment is associated with future perceptions of the economy. Thus, expansionary monetary policy might also stimulate aggregate demand through the bank lending channel by improving sentiment, which then contributes to increased loan demand. However, there is a potential trade-off for monetary policy: If positive sentiment is not associated with improved fundamentals, persistently loose monetary policy might contribute to excessive risk-taking when sentiment is positive, which might lead to an unsustainable increase in bank lending, the formation of asset price bubbles, and consequently a higher risk of financial instability (Ferguson et al., 2023; Grimm et al., 2023).

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Appendix

Appendix A: Consumer Survey Questions

Table A1: Consumer Confidence Index for the Present

Question	**Answer**
How has the financial situation of your household changed over the last 12 months?	$++$ got a lot better, $+$ got a little better, $=$ stayed the same, $-$ got a little worse, $--$ got a lot worse, N don't know
How do you think the general economic situation in the country has changed over the past 12 months?	$++$ got a lot better, $+$ got a little better, $=$ stayed the same, $-$ got a little worse, $--$ got a lot worse, N don't know
Which of these statements best describes the current financial situation of your household?	$++$ we are saving a lot, $+$ we are saving a little, $=$ we are just managing to make ends meet on our income, $-$ we are having to draw on our savings, $--$ we are running into debt, N don't know

Table A2: Consumer Confidence Index for the Future

Question	**Answer**
Compared to the past 12 months, do you expect to spend more or less money on major purchases (furniture, electrical/electronic devices, etc.) over the next 12 months?	$++$ much more, $+$ a little more, $=$ about the same, $-$ a little less, $--$ much less, N don't know
In view of the general economic situation, do you think that now it is the right moment for people to make major purchases such as furniture, electrical/electronic devices, etc.?	$++$ yes, it is the right moment now, $=$ it is neither the right moment nor the wrong moment, $--$ no, it is not the right moment now, N don't know
How do you expect the financial position of your household to change over the next 12 months?	$++$ get a lot better, $+$ get a little better, $=$ stayed the same, $-$ get a little worse, $--$ get a lot worse, N don't know
How do you expect the general economic situation in this country to develop over the next 12 months?	$++$ get a lot better, $+$ get a little better, $=$ stayed the same, $-$ get a little worse, $--$ get a lot worse, N don't know
How do you expect the number of people unemployed in this country to change over the next 12 months?	$++$ increase sharply, $+$ increase slightly, $=$ remain the same, $-$ fall slightly, $--$ fall sharply, N don't know

Appendix B: Additional Results

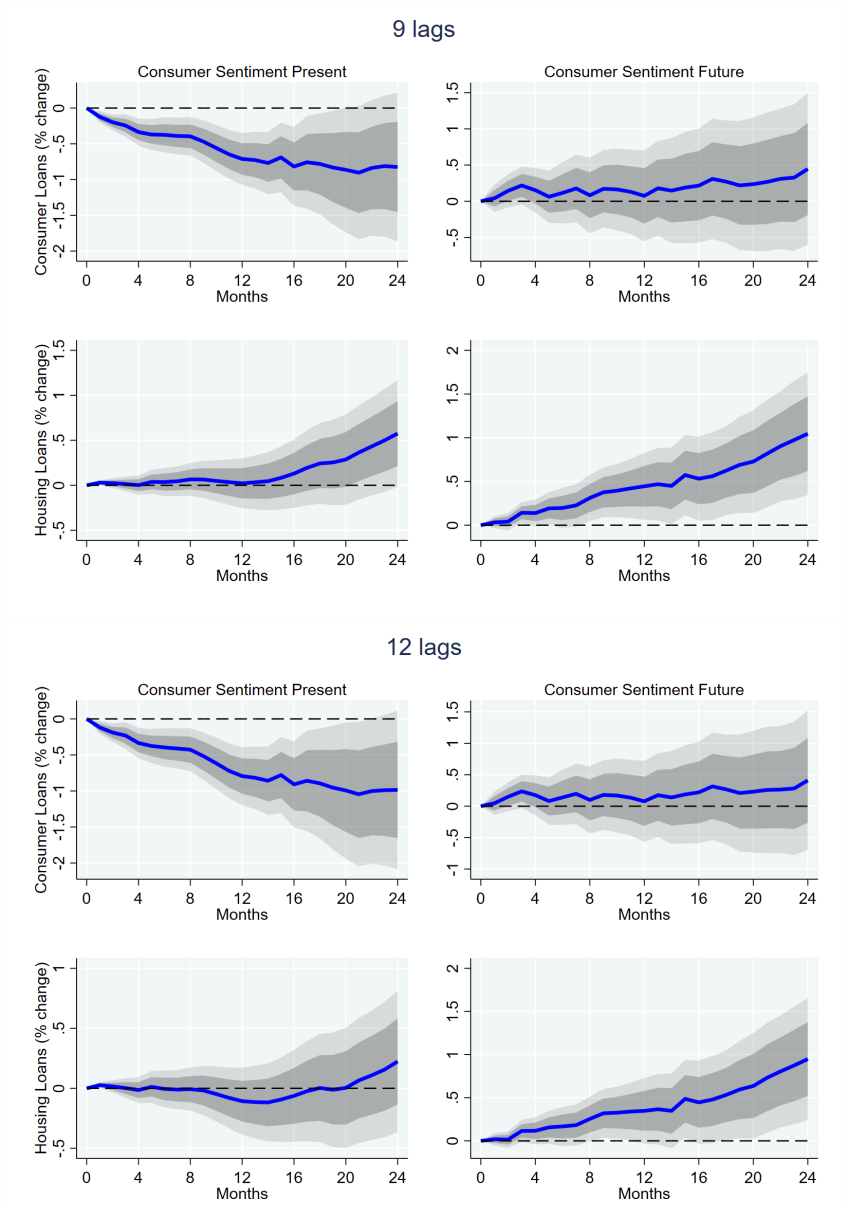
Table B1: Characteristics of news and pure (shock) consumer sentiment

Series	Type	Mean	SD	Skew.	Kurt.	Min.	25^{th}	Median	75^{th}	Max.	$\rho(1)$	$\rho(12)$	EL
SK Future	News	0.55	0.19	0.13	-1.00	0.23	0.38	0.55	0.72	1.06	0.97	0.52	***
	Pure	0.00	0.05	0.48	2.80	-0.20	-0.03	0.00	0.03	0.26	0.07	-0.08	
SK Present	News	0.57	0.16	0.02	-0.80	0.18	0.43	0.55	0.71	0.98	0.94	0.36	***
	Pure	0.01	0.07	4.44	32.90	-0.10	-0.03	0.00	0.02	0.68	0.15	-0.10	*
CZ Future	News	0.50	0.30	0.14	-1.30	-0.10	0.24	0.44	0.76	1.07	0.94	0.57	***
	Pure	0.01	0.15	0.84	4.20	-0.38	-0.08	0.00	0.09	0.83	0.01	0.11	
CZ Present	News	0.53	0.25	-1.31	8.10	-1.19	0.35	0.51	0.73	0.99	0.83	0.46	***
	Pure	0.00	0.20	2.23	50.10	-1.45	-0.07	-0.01	0.08	1.89	-0.18	0.09	
HU Future	News	0.51	0.32	-0.12	-1.20	-0.30	0.23	0.54	0.83	1.06	0.96	0.56	***
	Pure	0.00	0.13	1.39	8.60	-0.31	-0.07	0.00	0.07	0.90	0.07	0.03	
HU Present	News	0.54	0.32	-2.35	15.80	-1.98	0.34	0.58	0.78	1.05	0.78	0.30	***
	Pure	-0.02	0.32	4.83	84.00	-2.27	-0.08	-0.01	0.05	3.55	-0.24	0.05	
PL Future	News	0.62	0.27	-0.47	-1.00	-0.16	0.37	0.71	0.86	1.03	0.94	0.42	***
	Pure	0.00	0.17	1.71	10.60	-0.41	-0.09	-0.01	0.09	1.17	0.07	-0.03	
PL Present	News	0.59	0.26	-3.45	25.90	-1.73	0.46	0.63	0.77	0.91	0.72	0.18	***
	Pure	-0.01	0.27	3.03	58.80	-1.99	-0.09	-0.01	0.07	2.76	-0.23	0.07	
SI Future	News	0.51	0.24	0.28	-1.30	0.06	0.30	0.46	0.77	1.01	0.93	0.45	***
	Pure	0.01	0.14	0.47	3.20	-0.46	-0.06	0.00	0.08	0.70	0.04	-0.07	
SI Present	News	0.54	0.26	-1.33	7.90	-1.21	0.41	0.50	0.73	1.00	0.86	0.42	***
	Pure	-0.01	0.21	3.19	45.40	-1.34	-0.08	-0.02	0.04	2.03	-0.07	0.03	
HR Future	News	0.60	0.25	-0.26	-1.20	0.00	0.39	0.63	0.83	1.02	0.93	0.40	***
	Pure	-0.00	0.15	0.06	0.40	-0.45	-0.09	0.00	0.09	0.53	0.07	-0.02	
HR Present	News	0.64	0.24	-1.27	4.80	-0.74	0.48	0.65	0.83	0.99	0.81	0.22	***
	Pure	-0.02	0.19	3.42	39.10	-1.00	-0.08	-0.03	0.03	1.68	0.02	-0.01	
EE Future	News	0.52	0.29	-0.19	-1.40	-0.11	0.23	0.58	0.78	0.97	0.96	0.57	***
	Pure	0.03	0.13	0.44	3.10	-0.32	-0.04	0.04	0.09	0.71	0.09	-0.01	
EE Present	News	0.49	0.27	-3.11	23.30	-1.82	0.37	0.52	0.68	0.86	0.69	0.19	***
	Pure	0.02	0.29	3.95	80.50	-2.25	-0.06	0.01	0.09	3.23	-0.34	0.10	
LV Future	News	0.51	0.25	-0.61	-0.60	-0.13	0.35	0.56	0.73	0.96	0.94	0.42	***
	Pure	0.01	0.14	0.66	2.80	-0.40	-0.07	0.00	0.08	0.63	-0.08	0.01	
LV Present	News	0.52	0.25	-1.92	8.00	-1.17	0.42	0.57	0.69	0.89	0.83	0.28	***
	Pure	-0.01	0.22	2.75	46.40	-1.50	-0.09	-0.01	0.06	2.14	-0.13	-0.06	
LT Future	News	0.57	0.35	-0.31	-1.40	-0.11	0.25	0.62	0.91	1.06	0.97	0.41	***
	Pure	0.00	0.11	-0.07	1.00	-0.40	-0.07	0.00	0.07	0.34	0.24	-0.01	***
LT Present	News	0.61	0.26	-1.84	5.90	-0.96	0.53	0.67	0.79	1.00	0.85	0.35	***
	Pure	-0.01	0.19	3.87	57.60	-1.27	-0.08	-0.02	0.04	1.98	-0.08	-0.03	
BG Future	News	0.52	0.23	0.23	-1.10	0.06	0.32	0.48	0.71	0.98	0.92	0.46	***
	Pure	-0.01	0.15	0.56	1.50	-0.40	-0.10	-0.03	0.08	0.62	0.12	-0.04	
BG Present	News	0.55	0.20	-1.58	7.70	-0.76	0.43	0.58	0.69	0.95	0.75	0.36	***
	Pure	-0.01	0.23	5.10	66.90	-1.32	-0.10	-0.02	0.08	2.46	-0.17	0.02	
RO Future	News	0.56	0.32	-0.36	-1.20	-0.04	0.27	0.60	0.86	1.03	0.96	0.49	***
	Pure	0.00	0.13	0.68	1.50	-0.36	-0.09	-0.01	0.07	0.57	0.25	-0.05	***
RO Present	News	0.54	0.28	-1.45	7.10	-1.30	0.39	0.55	0.76	1.06	0.82	0.41	***
	Pure	-0.01	0.24	4.24	62.80	-1.56	-0.08	-0.01	0.06	2.52	-0.12	0.03	

Notes: The first, second and third quartiles are denoted as Q1, Q2 and Q3, respectively. $\rho(.)$ denotes the auto-correlation coefficient at the given order. The EL column shows the significance of the Escanciano and Lobato (2009) serial-correlation test (lag 12). All variables were tested for a unit root using Sul et al. (2005) and KPSS (1992). At the 10% level the null of no unit root was not rejected for any variable.

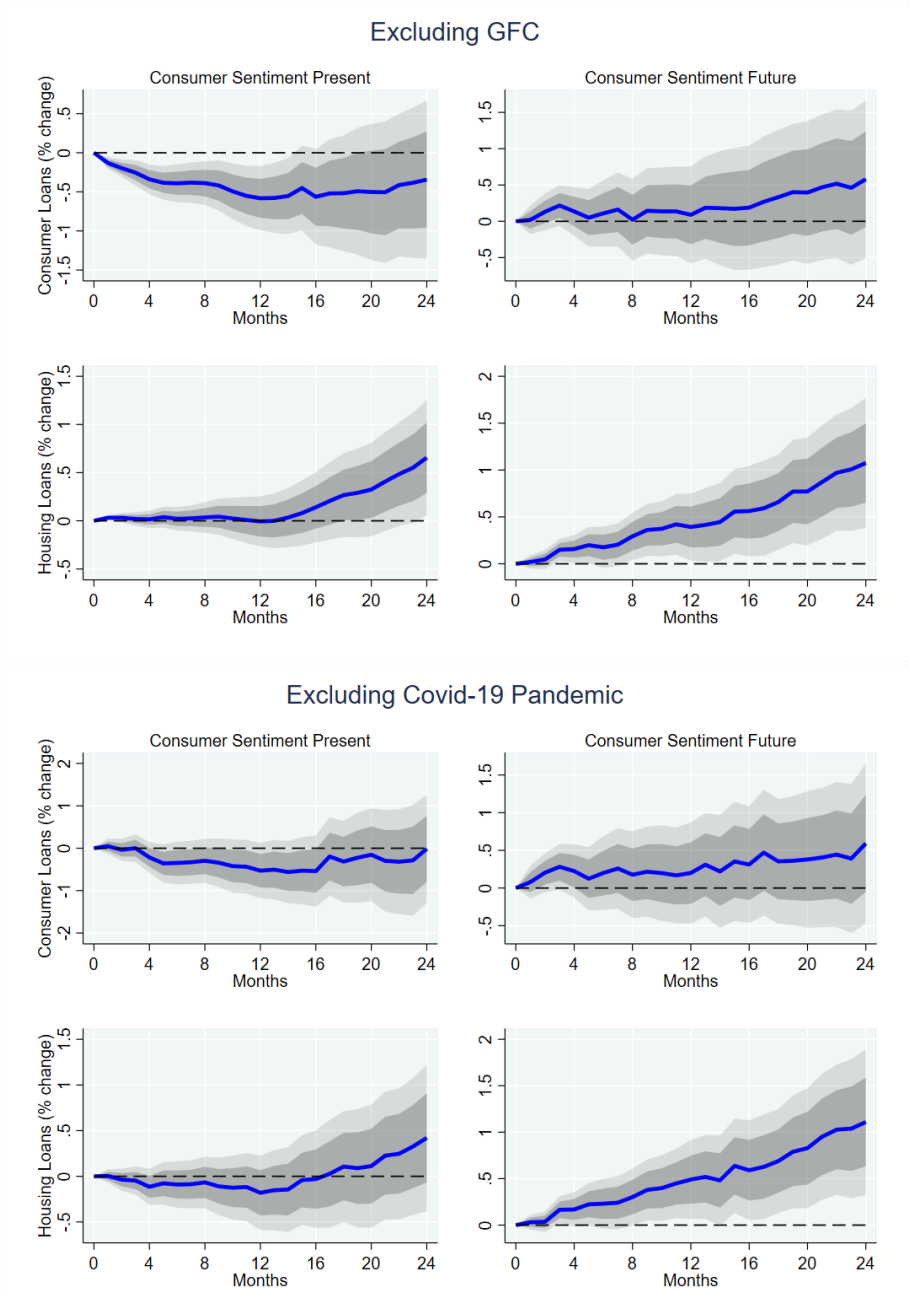
Appendix C: Robustness Checks

Figure C1: Different Number of Lags



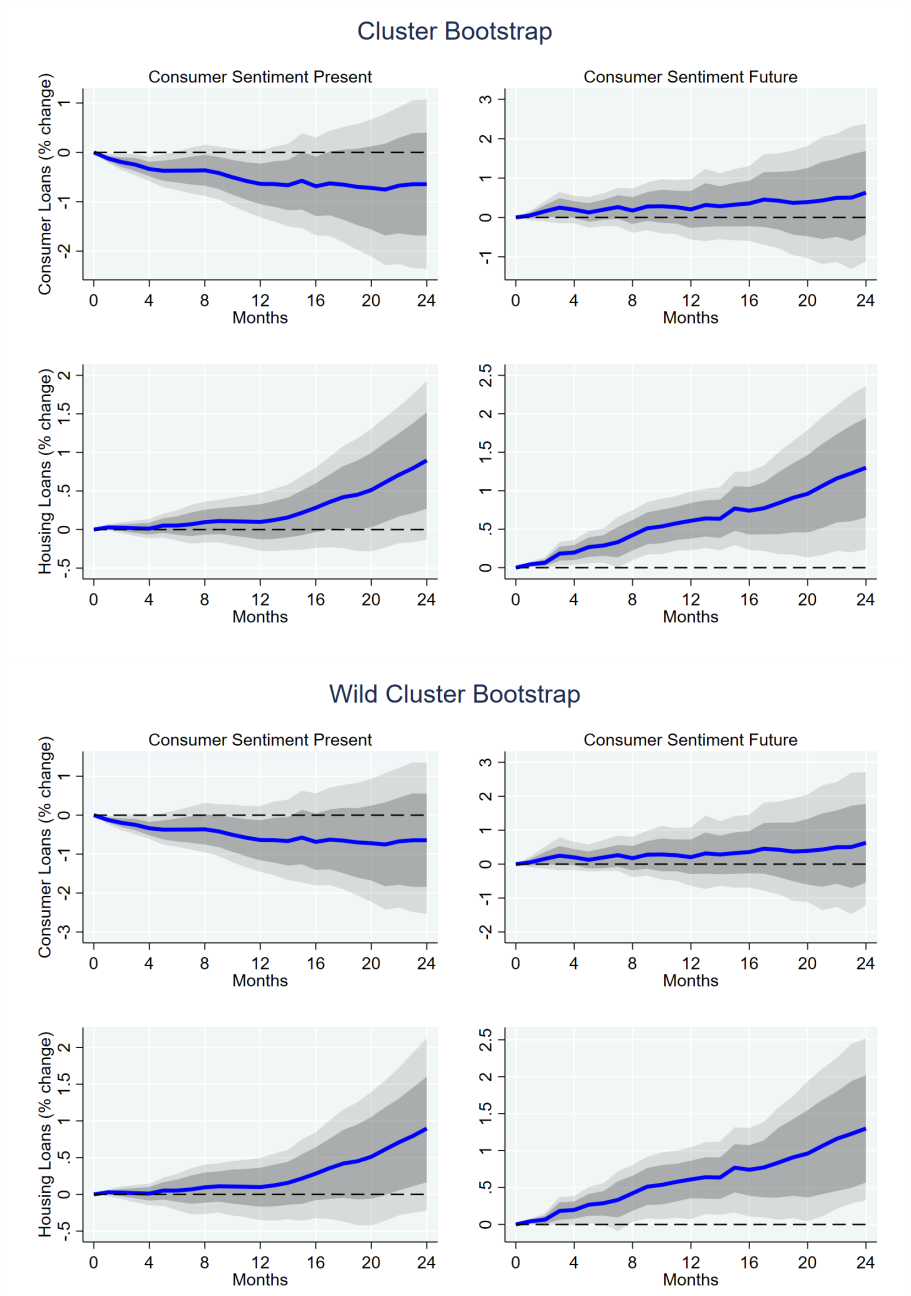
Notes: Cumulative IRFs of bank lending to pure sentiment shocks with different numbers of lags. The magnitude of the sentiment shock is standardized so that it represents a 1 in 20 (95^{th} percentile) increase in the respective sentiment measure. The solid line represents the point estimate, and the shaded areas correspond to 68 and 90 percent confidence bands. The point estimates are based on coefficients β_1^h from equation 5 over the entire forecast horizon $h = 1, \ldots, 24$. Month 1 ($h = 1$) is the first month after the sentiment shock. Driscoll-Kraay standard errors were used to calculate the confidence bands. Y-axis: deviation in percentage points. X-axis: time in months.

Figure C2: Different Time Periods



Notes: Cumulative IRFs of bank lending to pure sentiment shocks with different time periods. The magnitude of the sentiment shock is standardized so that it represents a 1 in 20 (95^{th} percentile) increase in the respective sentiment measure. *Excluding GFC* excludes the years 2008-2009 (i.e., the sample starts in 2010), while *Excluding Covid-19 Pandemic* excludes the year 2020, as the pandemic's first year with the most pronounced economic fluctuations. The solid line represents the point estimate, and the shaded areas correspond to 68 and 90 percent confidence bands. The point estimates are based on coefficients β_1^h from equation 5 over the entire forecast horizon $h = 1, \ldots, 24$. Month 1 ($h = 1$) is the first month after the sentiment shock. Driscoll-Kraay standard errors were used to calculate the confidence bands. Y-axis: deviation in percentage points. X-axis: time in months.

Figure C3: Bootstrapped Standard Errors



Notes: Cumulative IRFs of bank lending to pure sentiment shocks with bootstrapped standard errors. The magnitude of the sentiment shock is standardized so that it represents a 1 in 20 (95^{th} percentile) increase in the respective sentiment measure. The solid line represents the point estimate, and the shaded areas correspond to 68 and 90 percent confidence bands. The point estimates are based on coefficients β_1^h from equation 5 over the entire forecast horizon $h = 1, \ldots, 24$. Month 1 ($h = 1$) is the first month after the sentiment shock. Confidence bands were constructed based on bootstrapped standard errors with 500 iterations. Y-axis: deviation in percentage points. X-axis: time in months.