Sentiment Driven Loans*

Boris Fišera[†a,b], Zuzana Košťálová[a], and Štefan Lyócsa[a,c]

[a]Institute of Economic Research, Slovak Academy of Sciences, Bratislava
[b]Institute of Economic Studies, Charles University, Prague
[c]Faculty of Economics and Administration, Masaryk University, Brno

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Abstract

Consumer sentiment affects economic growth by influencing consumption and investment choices. We explore one of the channels through which sentiment influences the economy, demand for loans. We create fundamental-driven and pure sentiment indices using several data-driven machine learning (ML) techniques. Fundamental-driven sentiment is the predicted sentiment from ML models augmented with numerous macro-financial variables. Forecast errors from ML models serve as our proxy for unexpected sentiment shocks, pure sentiment. Next, using local projections approach and a panel of Central European economies, we find that positive shocks to sentiment contribute to an increase in housing loans, while sentiment has a limited effect on consumer loans. Moreover, sentiment about future economic conditions has a greater effect on loans than sentiment about present economic conditions. Finally, we find that monetary policy stance influences the effect of sentiment: Sentiment only affects bank lending when monetary policy stance is persistently loose.

Keywords: sentiment, bank lending, consumer loans, housing loans, monetary policy, machine learning

JEL Codes: C53, G21, G51

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†Corresponding author's address: Institute of Economic Research, Slovak Academy of Sciences, Sancova 56, Bratislava, 811 05, Slovak Republic; e-mail: boris.fisera@savba.sk

1 Introduction

A growing body of research has examined the survey-based sentiment measures, as the information they contain might not otherwise be captured by other hard economic data. Survey-based sentiment indicators provide information not only about past economic developments but also on the current and future behaviour of different economic agents (firms and consumers). They contain information on agents' perceptions and expectations of future economic conditions (DG ECFIN, 2024). Furthermore, sentiment indicators could signal elevated levels of uncertainty (Vuchelen, 2004).

A large body of this literature investigated the link between the sentiment and economic activity or consumer spending. For instance, Matsusaka and Sbordone (1995), Batchelor and Dua (1998) and Christiansen et al. (2014) found that Michigan's Index of Consumer Sentiment could be a useful tool in forecasting economic fluctuations. Beaudry et al. (2011) suggest that the swings in consumer optimism and pessimism are important drivers of business cycles. However, it remains challenging to distinguish whether these mood swings are rationally founded or whether they merely reflect self-fulfilling beliefs.

Conversely, the findings of Barsky and Sims (2012) suggest that consumer confidence indicators containing fundamental news can be used as a predictor of future macroeconomic variables, whereas overly optimistic or pessimistic moods of consumers – otherwise termed animal spirits or false shocks – do not predict business cycle fluctuations. Constantinides et al. (2023) identify 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, due to less efficient financial markets, economic agents in these countries have greater difficulty distinguishing pure sentiment from fundamentals. Carroll et al. (1994), Bram and Ludvigson (1998) and Nahuis and Jansen (2004) posit that sentiment indicators contain information on future consumer spending and can be used to forecast consumption.

In this paper, we assume that such surveys could also have the potential to reflect expectations of economic agents regarding the future development of the credit market and their 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 the current consumption if they are optimistic about their future income. Negative sentiment may indicate a higher uncertainty, which could in turn impact lending decisions on the part of businesses and households (Košt'álová et al., 2022).

The existing literature on the drivers of credit growth is extensive, with different variables being identified as drivers of credit growth: interest rates (Hofmann, 2001; Elekdag and Wu, 2013; Gozgor, 2018), unemployment rate (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 a "traditional" set of credit drivers, there is a recent body of literature, which uses a 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 the impact of the EPU on credit (Bordo et al., 2016; Caglayan and Xu, 2019; Danisman et al., 2020; Košt'álová et al., 2022).

Nevertheless, the role of sentiment in influencing bank lending remains relatively underexplored. Delis et al. (2014) investigate how banks' lending behaviour changes during anxious periods, which are defined as periods of high uncertainty when expectations of economic agents 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. As Rychtárik (2018) observes, business and consumer surveys have been shown to be useful indicators of future excessive credit growth in the economy. Building on this, Košt'álová et al. (2022) argue that desegregated survey-based sentiment may be more relevant and appears to predict the creation of new loans. Gric et al. (2022) introduced a novel approach to explain the role of sentiment in the growth of consumer loans. The sentiment is decomposed into rational and irrational components. The rational component is driven by macroeconomic fundamentals, while the irrational component serves as a proxy for the mood of excessive optimism or pessimism. They found that the irrational sentiment exerts an asymmetric effect on bank lending, with positive effect on consumer loans only occurring during an upward business cycle.

In this paper, we explore the role of consumer sentiment in affecting bank lending in four Central European (CE) countries, namely the Czech Republic, Hungary, Poland and Slovakia. These economies underwent a comparable transition process towards the market economy and have experienced substantial growth of household credit over the past three decades. This paper proposes a novel approach to identify shocks to consumer sentiment. Furthermore, we construct two sentiment indices that reflect consumers' sentiment about the present economic conditions and about the future economic conditions. Next, we use the local projections approach to estimate the impulse responses of bank lending to shocks to present and future sentiment. We estimate our regressions both for a panel of CE countries and separately for each country in the sample.

We extend the existing literature on the role of sentiment in credit expansion in several ways. First, we distinguish between the effect 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 investments. Second, we disaggregate consumer sentiment, assuming that sentiment about the present and sentiment about the future play a different role in households' spending and saving intentions. Third, to identify sentiment shocks, we decompose our measure of consumer sentiment into the sentiment component driven by economic fundamentals and the sentiment component that is orthogonal with respect to fundamentals. We call the latter component *pure sentiment* and we use it as our proxy for sentiment shocks. In contrast to Gric et al. (2022), we use machine learning techniques to identify the fundamental-driven (or rational) component of consumer sentiment. Next, forecast errors serve as a proxy for pure sentiment.

We find evidence that consumer sentiment influences households' demand for loans. Positive sentiment shock has a positive effect on housing loans that is moderate in size, while the effect on consumer loans is negligible. The sentiment about the future has a larger effect on bank lending than the sentiment about the present. Moreover, the effect of sentiment on bank lending varies with the prevailing monetary policy stance: Consumer sentiment only influences bank credit when monetary policy stance is loose. With contractionary monetary policy stance sentiment does not influence bank lending. Finally, even in our sample of rather homogeneous CE countries, the effect of sentiment on bank lending is quite heterogeneous across the different countries.

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. Additional results can be found in the Appendix.

2 Data

Our study uses monthly data from four Central European (CE) countries: the Czech Republic, Hungary, Poland, and Slovakia, collectively referred to as the Visegrad Group or V4 countries. The countries in our sample have experienced comparable socio-economic development: They are 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 the property markets starting in the 1990s. In all four countries, there has been an unprecedented rise in the provision of household credit over the past three decades.

Our monthly data for consumer and housing loans end in September 2024, though it begins at different times for each country: February 2006 for Slovakia, January 2002 for Czech Republic, January 2005 for Hungary and March 2009 for Poland. We create two indices of consumer sentiment about the present and the future based on a harmonised consumer survey published by the Directorate-General for Economic and Financial Affairs (DG ECFIN). See Tables A1 and A2 for details of the questions used to construct sentiment indices. However, in order to decompose the sentiment, we use sentiment data from as early as January 2002 for each respective country. An advantage of these consumer surveys is that the data are readily available, provided at high frequency, and standardized across European Union countries.

3 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.

3.1 Sentiment Shock Identification

3.1.1 Sentiment Decomposition

To construct our measure of consumer sentiment, we use the data from the harmonised consumer survey. Based on 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 (Baker and Wurgler, 2006; Baker et al., 2012; Constantinides et al., 2023; 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*, while $S_t^{\perp}$ is the sentiment component that is orthogonal to economic fundamentals. Following Constantinides et al. (2023), we refer to this component as the *pure sentiment*.[1] The higher-level representation of the decomposition of sentiment to the fundamental-driven and pure sentiment can be represented by:

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

where $\boldsymbol{Z}$ is a matrix of economic fundamentals that could predict the consumer sentiment and I_{t-1} denotes an information set, i.e., all data are known one month before we observe the sentiment at time t. Finally, the function $f(.)$ represents predicted values from a given model. The predicted values from equation 2 can be perceived as fundamental-driven sentiment ($\hat{S}_t \equiv S_t^E$), 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 vary by country, we estimate the model given in equation 2 separately for each country in our sample. The set of economic fundamentals varies by each country in the sample. The same set consists of: i) changes in consumer and ii) housing loans, iii) future and iv) past sentiment, v) unemployment rate, vi) percentage changes in the harmonized index of consumer prices, vii) Euro Area shadow rate, viii) current account deficit to GDP, ix) changes in the industrial production index, x) composite indicator of systemic stress, xi) household loans interest rate in the Euro Area, xii) monthly EUREX realized daily volatility, xiii) implied volatility index VIX, xiv) macro-prudential policy index[2] and xv) linear time-trend.

For Slovakia, the specific variable was the interest rates on new loans to households. For Czech Republic: house price index, 3M PRIBOR (Prague InterBank Offered Rate), percentage changes in the EUR/CZK exchange rate, For Hungary: house price index, 3M interest rate, percentage changes in the HUF/EUR exchange rate. For Poland: percentage changes in the PLN/EUR exchange rate, WIG volatility index, changes in the new EUR loans to households. Each of the models uses values at lag 1, 2, 3, and 12 to account for short-term persistence and potential seasonal effects.

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

[2] An index indicating cumulative change in tightening (+1) or loosing (-1) macro-prudential policy measures as indicated via changes in the countercyclical capital buffer - effective, capital conservation buffer – effective, loan-to-value and debt service-to-income ratio.

3.1.2 Sentiment Forecasts

To approximate the unknown function $f(.)$ we use a random walk model as our benchmark and five data-driven methods to estimate the equation 2. We use three penalized regression models, the LASSO, Ridge and the Elastic net, which are represented by:

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

where S_t is the given measure of sentiment, $Z_{k|I_{t-l}}$ are lagged fundamentals (with $l = 1, 2, 3, 12$). The two hyper-parameters are the $\lambda > 0$, which is the penalty term and $\alpha = 1$ for LASSO of Tibshirani (1996), $\alpha = 0$ for Ridge model of Hoerl and Kennard (1970b,a) and we consider $\alpha \in (0.2, 0.4, 0.6, 0.8)$ for elastic net of Zou and Hastie (2005).

The fourth 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 less than 5 observations; a minimum required for a split. We use two hyper-parameters: 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 node (out of 69 explanatory variables), ii) the number of trees $(50, 100, 250, 500, 1000)$. Consider having 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's prediction is the averaged across all trees generated from different bootstrap samples:

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

The fifth model is the boosted regression tree. Given a set of variables $\boldsymbol{Z}|I_{t-1}$ and the sentiment S_t, we estimate a regression tree denoted by $T_t^0(S_t, \boldsymbol{Z}|I_{t-1})$. The predicted observations are given by $\hat{S}_{t,T^0}$ and corresponding errors as $R_t^0 = S_t - \hat{S}_{t,T^0}$. An updated prediction is given by $S_t^{b=1} = \hat{S}_{t,T^0} + \eta R_t^0$, where $\eta > 0$ is the learning rate. A sequence $(b = 1, 2, ..., B)$ of regression trees follow, where the subject of interest are residuals from the previous model. We consider $\eta \in (0.10, 0.01, 0.001)$ as potential learning rates, $B \in 250, 500, 1000$ as number of trees and $D \in (2, 4, 6)$ as maximum depth of the tree; all hyper-parameters.

The hyper-parameters are being estimated for each model using an expanding estimation window size that starts with 42 months. Additional 18 month are used to observe the out-of-sample performance, measured via mean square error, of the model under different hyper-parameter settings. The model with hyper-parameters that led to the lowest mean-square error is selected for the next period predictions. Specifically, the first true out-of-sample prediction is given for the 61^{st} observation. After that, all models are re-estimated, mean-square-errors over the past 18 month re-evaluated and potentially a new suitable combination of hyper-parameters is being employed.

The final prediction $\widehat{S}_t$ that corresponds to sentiment driven by economic fundamentals, is given as an arithmetic average of all six model forecasts. This approach was advocated by as early as by Bates and Granger (1969); Granger and Ramanathan (1984) and a bit more recently by Timmerman (2006) arguing that not only it diversifies against model choice uncertainty, but that a suitable ensemble can even lead to lower (mean-square) forecast errors if individual forecasts are unbiased and not highly correlated. We follow these recommendations and use the simple average forecast from the six models (including the random walk approach) to predict the new-based sentiment.

3.2 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 time period. We begin our analysis by estimating the following equation for a panel of the 4 Central European countries in our sample:

$$\begin{aligned} y_{i,t+h} - y_{i,t} = \alpha_i^h + \beta_1^h \epsilon_{i,t}^s + \beta_2^h \widehat{S_{i,t}} + \gamma'^h X_{i,t} + \delta_{1j}^h \sum_{j=1}^{2} \epsilon_{i,t-j}^s + \delta_{2h}^h \sum_{h=1}^{hmax} \epsilon_{i,t+h}^s \\ + \delta_{3k}^h \sum_{k=0}^{2} (y_{i,t-k} - y_{i,t-k-1}) + \nu_{i,t+h}, \;\; for \;\; h = 1, \ldots, 12 \end{aligned} \tag{5}$$

where $y_{i,t}$ is our proxy for bank loans in country i in month t. In our regressions, we distinguish between consumer loans ($y_{i,t}^C$) and housing loans ($y_{i,t}^H$). That is, $y_{i,t} \in (y_{i,t}^C, y_{i,t}^H)$. $\epsilon_{i,t}^s$ are the residuals from equation 2, which serve as our measure of orthogonal sentiment shocks[3], while $\widehat{S_{i,t}}$ stands for the sentiment driven by economic fundamentals. X is a vector of control variables that might influence bank lending[4] and α_i are country

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

[4]The control variables include: CBOE Volatility Index, spread between the yield of a 10-year government bond vis-à-vis Germany, 3-month interbank interest rate, exchange rate of domestic currency

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 $h = 1, \ldots, 12$ 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 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-based (fundamental-driven) sentiment ($\widehat{S_{i,t}}$) in all the regression specifications.

Equation 5 enables us to generalize the relationship between consumer sentiment and bank lending in the 4 Visegrad countries. Although the 4 CE economies share many common traits, estimating equation 5 in a panel setting could disguise important heterogeneities between the CE countries.[5] Therefore, in the next step of our analysis, we re-estimate equation 5 country-by-country:

$$\begin{aligned} y_{t+h} - y_t = \alpha^h_0 + \beta^h_1 \epsilon^s_t + \beta^h_2 \widehat{S}_t + \gamma'^h X_t + \delta^h_{1j} \sum_{j=1}^{2} \epsilon^s_{t-j} + \delta^h_{2h} \sum_{h=1}^{hmax} \epsilon^s_{t+h} \\ + \delta^h_{3k} \sum_{k=0}^{2} (y_{t-k} - y_{t-k-1}) + \nu_{t+h}, \ \ for \ \ h = 1, \ldots, 12 \end{aligned} \tag{6}$$

Estimating the equation 6 separately for each country in our sample enables us to generate country-level impulse responses of loans to sentiment shocks.

3.2.1 Role of Monetary Policy

Monetary policy stance is one of the key determinants of bank lending, and the interaction between sentiment and monetary policy has already been highlighted by Kashyap

against the Euro (U.S. dollar in the case of Euro Area member Slovakia), inflation rate, industrial production index as a proxy for monthly real economy developments, Euro Area shadow rate, an index for changes in macro-prudential policy, and quarterly seasonal dummies.

[5] Furthermore, a panel with just 4 countries could suffer from limited generalizability.

and Stein (2023). Therefore, in the following step of our empirical analysis, we study whether the stance of monetary policy influences the effect of sentiment on bank lending. Namely, 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 rate of interest ($r^*_{i,t}$) as the sum of the world 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 actual short-term real rate from the natural rate:

$$\overline{stance}_{i,t} = \frac{1}{12} \sum_{l=0}^{12} (r_{i,t-l} - r^*_{i,t-l}) \tag{7}$$

where $\overline{stance}_{i,t}$ captures whether monetary policy has been tight or loose over the previous 12 months, while r stands for 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 looser or tight by estimating the following equation:

$$\begin{aligned} y_{i,t+h} - y_{i,t} = \alpha_i^h + \beta_{1e}^h \epsilon_{i,t}^s \mathbb{I}_{i,t} + \beta_{1r}^h \epsilon_{i,t}^s (1 - \mathbb{I}_{i,t}) + \beta_2^h \widehat{S_{i,t}} + \gamma'^h X_{i,t} + \delta_{1j}^h \sum_{j=1}^{2} \epsilon_{i,t-j}^s \\ + \delta_{2h}^h \sum_{h=1}^{hmax} \epsilon_{i,t+h}^s + \delta_{3k}^h \sum_{k=0}^{2} (y_{i,t-k} - y_{i,t-k-1}) + \nu_{i,t+h}, \ \ for \ \ h = 1, \ldots, 12 \end{aligned} \tag{8}$$

where $\mathbb{I}_{i,t}$ is the indicator variable that takes the value of 1 when the monetary policy stance in the given country in the given month was expansionary ($\overline{stance}_{i,t} < 0$), and 0 otherwise. Therefore, coefficients β_{1e}^h enable us to generate impulse responses of bank lending to sentiment shocks when monetary policy is expansionary, while coefficients β_{1r}^h represent the response of bank lending to sentiment shocks when monetary policy is contractionary.

4 Empirical Results

4.1 Stylized Facts

We first provide some stylized facts on our key variables of interest: housing and consumer loan developments, and decomposed news-based sentiment and pure sentiment indicators.

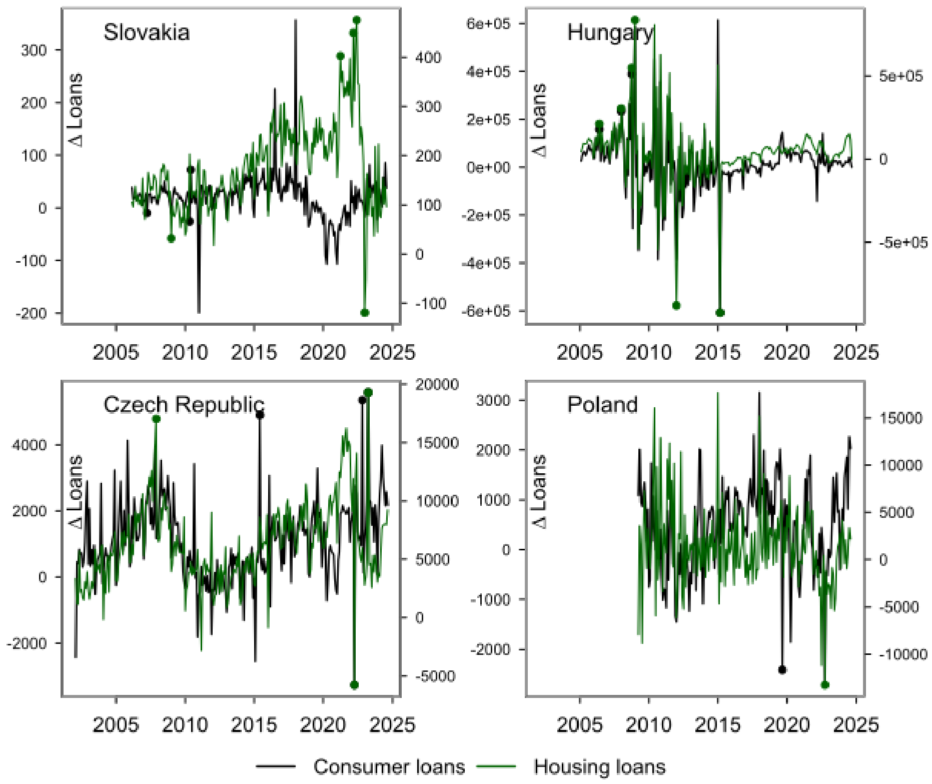
4.1.1 Household and Consumer Loans: Heterogeneous Dynamics

Visualization of loan changes (see Figure 1 shows different loan dynamics across the countries in our sample. Several known events can be observed in the data. For example, in Slovakia housing and consumer loans show very different dynamics particularly after 2016, which can be attributed to the lower interest rates and '*lex Beblavy*' (Košt'álová et al., 2022) that simplified the refinancing of existing loans. The correlation between consumer and housing loans is -0.038. These points appear mostly during the global financial crisis and the COVID pandemic. Housing and consumer loans also show high level of co-movement in Hungary, at 0.93, in Czech Republic at 0.52 and in Poland still significant at 0.29 of Pearson's correlation.

In Hungary, the reform in 2015 eliminated foreign exchange loans has helped to stabilize bank lending, which is visible from Figure 1. In fact, using the Inclan and Tiao (1994) algorithm with the Sansó et al. (2004) test, we identified one volatility break in the series in February 2015.

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. Results in Table 1 reveal several stylized facts about loans: i) hosing loans do not show severe persistence, ii) they are seasonal (except Hungary), iii) they are subject to sudden shocks (see Kurtosis). Given the slow-pacing nature of key economic variables, like interest rates, unemployment rate or economic growth, it might be that such shocks are driven by other than rationally expected changes in fundamentals of the underlying economy.

Figure 1: Monthly Changes in Consumer and Housing Loans



Notes: Highlighted dots correspond to smoothed observations.

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												
Δ Consumer Loans	25	83	9.3	117.3	-199	5	23	37	1075	0.05	0.08	***
Δ Housing Loans	162	268	-12.4	175.1	-3585	111	166	230	544	0.13	0.02	***
News-driven future sentiment	0.53	0.17	-0.05	1.56	0.22	0.37	0.49	0.71	0.79	0.98	0.51	***
Pure future sentiment	0.00	0.05	0.17	3.70	-0.16	-0.03	0.00	0.03	0.17	0.26	-0.05	***
News-driven present sentiment	0.55	0.15	-0.41	2.39	0.10	0.43	0.56	0.70	0.83	0.94	0.24	***
Pure present sentiment	0.01	0.07	4.18	32.18	-0.11	-0.03	0.00	0.02	0.64	0.17	-0.06	**
Panel B: Czech Republic												
Δ Consumer Loans	1097	1344	1.3	11.2	-4282	307	957	1865	9747	0.32	0.27	***
Δ Housing Loans	6323	3792	0.4	9.1	-15047	3938	5917	8394	24535	0.51	0.30	***
News-driven future sentiment	0.48	0.29	0.20	1.86	-0.16	0.25	0.42	0.77	1.04	0.94	0.62	***
Pure future sentiment	0.00	0.15	0.71	7.71	-0.44	-0.08	0.00	0.07	0.84	0.04	0.10	
News-driven present sentiment	0.52	0.24	-1.41	12.54	-1.11	0.36	0.49	0.69	0.96	0.82	0.47	***
Pure present sentiment	0.01	0.20	2.17	46.63	-1.39	-0.08	0.00	0.08	1.83	-0.11	0.12	
Panel C: Hungary												
Δ Consumer Loans	16330	170296	-2.7	40.9	-1601383	-22547	19820	62065	943454	0.11	0.13	
Δ Housing Loans	29155	244541	-2.8	32.8	-2151252	-19188	39002	93163	1079083	0.17	0.11	
News-driven future sentiment	0.54	0.32	-0.24	2.10	-0.39	0.28	0.56	0.84	1.09	0.96	0.53	***
Pure future sentiment	0.00	0.14	1.32	11.35	-0.40	-0.07	0.00	0.08	0.91	0.11	0.02	
News-driven present sentiment	0.56	0.30	-1.58	10.13	-1.32	0.40	0.59	0.80	1.03	0.84	0.26	***
Pure present sentiment	-0.01	0.30	6.85	93.31	-1.60	-0.09	-0.01	0.05	3.48	-0.18	0.05	
Panel D: Poland												
Δ Consumer Loans	433	980	-1.4	10.3	-5662	-179	469	1012	3154	0.39	0.22	***
Δ Housing Loans	1406	4366	0.4	5.8	-15504	-949	1080	3414	17683	0.06	0.08	
News-driven future sentiment	0.60	0.27	-0.36	1.88	-0.13	0.36	0.66	0.85	1.00	0.95	0.38	***
Pure future sentiment	0.00	0.18	1.72	13.33	-0.45	-0.11	-0.01	0.09	1.20	0.16	0.00	**
News-driven present sentiment	0.57	0.29	-4.86	45.01	-2.23	0.46	0.60	0.74	0.90	0.66	0.10	***
Pure present sentiment	-0.01	0.30	0.85	56.66	-2.49	-0.08	0.00	0.07	2.73	-0.20	0.07	

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.

These results show that loan dynamics is quite different between countries not only in terms of co-movement between consumer and housing loans, but also in terms of persistence, which in turn implies different shock absorption behaviour. A common feature across loans seems to be, that loan dynamics is subject to frequent shocks in both directions.

4.1.2 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 of six models. Table 2 reports forecasting accuracy results from the six individual models. In the first column we show the mean square error from the naïve random-walk model. Values in the remaining columns show percentage improvements (a positive number) in forecast accuracy compared to the random-walk models. For example, the value of -5.5 in Panel A for the row '*Future sentiment*' means that LASSO under-performed random walk by 5.5% in terms of mean square error. Many negative numbers in the Table 2 suggest that the naïve random-walk model of sentiment is actually difficult to beat. The result implies that current values of sentiment might already reflect most economic fundamentals. However, using combination forecast (column CF) systematically out-performs the naïve model in all cases, with forecast improvements ranging from just 0.3% for present sentiment in Poland (Panel D) to 27.0% for future sentiment in Slovakia.

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 along with loan characteristics in Table 1. 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 (from 0.66 for news-driven present sentiment in Poland to 0.98 for news-driven future sentiment in Slovakia), while pure sentiment is, as expected, much nosier and subject to large spikes, which are clustered in the global financial crisis and COVID periods.

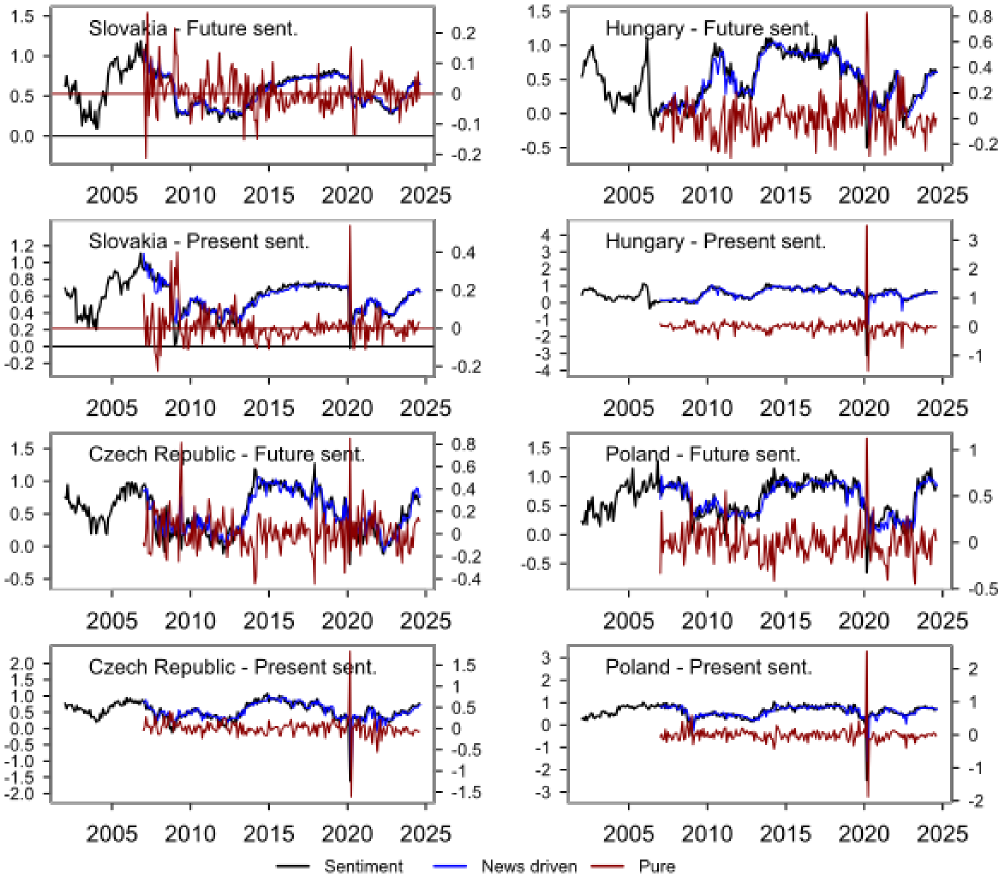
In summary, similarly to loan dynamics, sentiment also seems to behave distinctively across the four countries. News-driven sentiment changes slowly, while pure-sentiment is much noisier and subject to sudden shocks. In the next section, we apply the local projection framework of Jorda (2005) to formally explore the effect of consumer sentiment on consumer and housing loans.

Table 2: Consumer Sentiment Mean Square Forecast Errors

	RW	LASSO	RIDGE	EN	RF	XGB	CF
Panel A: Slovakia							
Future sentiment	0.0034	-5.5	-74.8	-10.8	-1.1	-1.8	27.0
Present sentiment	0.0061	0.3	-35.4	1.4	-18.5	-13.7	10.1
Panel B: Czech Republic							
Future sentiment	0.0243	-9.2	-23.8	-10.8	-0.7	-12.9	7.9
Present sentiment	0.0422	-5.0	-11.1	0.8	13.8	-6.9	4.8
Panel C: Hungary							
Future sentiment	0.0202	-6.4	-22.6	-7.8	4.2	-1.9	6.1
Present sentiment	0.1221	-6.4	19.9	14.9	25.2	26.2	25.0
Panel D: Poland							
Future sentiment	0.0327	-3.4	-8.6	-2.9	8.2	0.1	5.6
Present sentiment	0.0921	-28.5	-4.9	-12.5	21.4	28.1	0.3

Notes: In the column RW we report the mean square error of the random-walk model (our benchmark) that predicts the sentiment (in a given row). In the remaining columns, we show percentage improvements (positive values) in forecasting accuracy, from five models: LASSO, Ridge, Elastic Net (EN), Random forest (RF) and Boosted regression tree (XGB). The final column is the combination forecast (a simple average) of the individual model forecasts (including the random walk). We use combination forecasts to decompose sentiments into news-based sentiment and pure sentiment.

Figure 2: Fundamental-driven Sentiment and Pure Consumer Sentiment.



4.2 Consumer Sentiment and Bank Loans

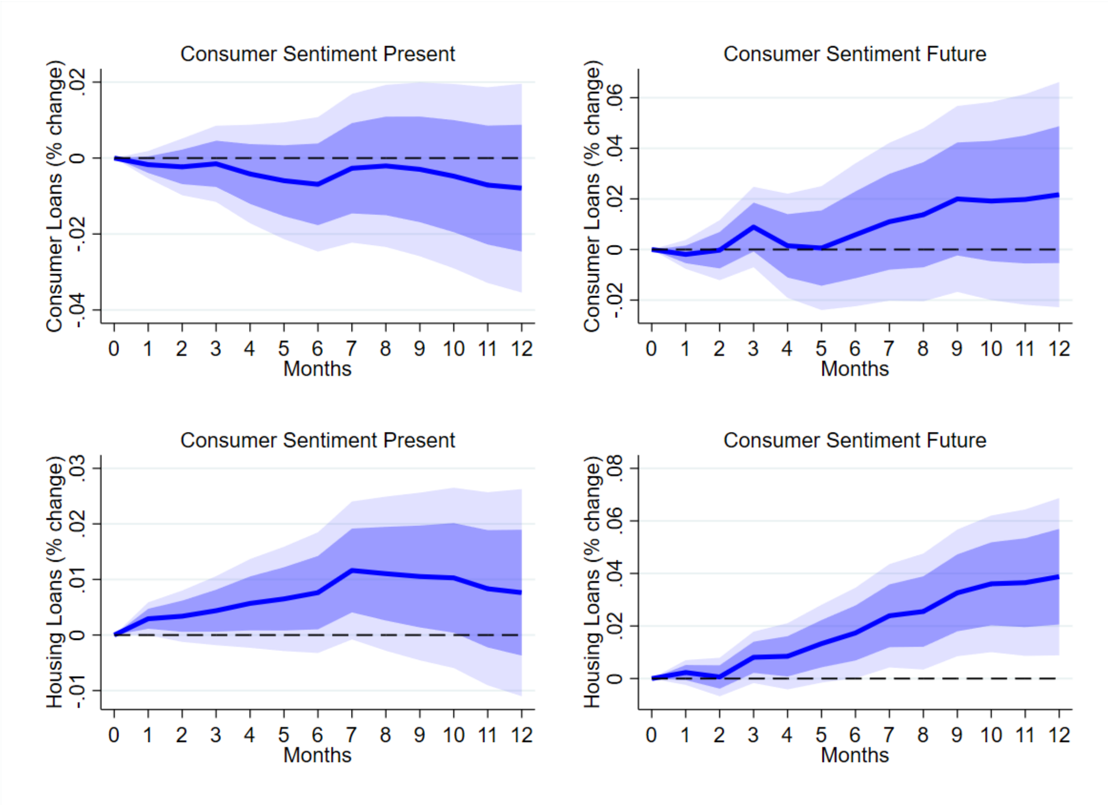
In the following sub-section, we report our findings on the effect of consumer sentiment on bank lending. First, we report the results for the panel of CE countries. Second, we report the country-specific results.

The results of baseline regressions on the effect of pure sentiment shocks[6] for the panel of CE countries are reported in Figure 3. We find that the effect of pure sentiment shocks have limited effect on consumer loans: Shocks to present sentiment have a small negative effect on consumer loans, which is not statistically significant. Shocks to future

[6]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-based (fundamental-driven) sentiment in all regression specifications.

sentiment have no effect on consumer loans during the first six months following the shock, and while this effect turns positive after six months, it is barely statistically significant. The effect of a shock to future sentiment also has a small magnitude: A 1 in 12 increase in pure sentiment about the future (i.e., an increase in sentiment that occurs on average every 12 months, or 92^{nd} percentile) increases consumer loans cumulatively by mere 0.33% over a period of 12 months.

Figure 3: Effect of Pure Sentiment on Bank Lending – Panel of CE Countries



Notes: Cumulative IRFs of bank lending to pure sentiment shocks. 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 point estimate, shaded areas correspond to 68 and 90 percent confidence bands. The point estimates are the coefficients β_1^h from equation 5 over the entire forecast horizon $h = 1, \ldots, 12$. Month 1 ($h = 1$) is the first month after the sentiment shock. The standard errors used to calculate these confidence bands were clustered at a country level. Y-axis: deviation in percentage points. X-axis: time in months.

The bottom panel of Figure 3 depicts the responses of housing loans to sentiment shocks. For housing loans, the effect of sentiment shocks seems to be larger: Positive sentiment leads to a persistent increase in housing loans that is also statistically significant. As with consumer loans, the shocks to sentiment about the future have a more positive effect on housing loans than the shocks to sentiment about the present: A 1 in 12 (92^{nd} percentile) increase in present and future sentiment leads to a cumulative increase in housing loans over a 12-month period by 0.10% and 0.54%, respectively. As housing loans in our panel of CE economies increase on average by some 5% over a 12-month period, a large positive shock to sentiment about the future can increase housing loans' *rate of growth* by approximately one tenth.

To conclude, our results indicate that sentiment shocks have a larger effect on housing loans than on consumer loans and that sentiment about the future has a larger effect on loans than sentiment about the present. The latter finding hinges on our ability to properly distinguish between present and future sentiment. Namely, 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 (0.44) – underlining the importance of distinguishing properly between present and future sentiment.

Therefore, to ensure that our findings on the larger effect of future sentiment are robust, in the next step of our analysis, we eliminate the common component of present and future sentiment by taking the difference between the two sentiment measures and using this difference as an alternative measure of sentiment about the future – *relative future sentiment*.[7] Next, we re-estimate our baseline regressions with this relative future sentiment instead of our baseline future sentiment shock measure, and we report the results in Figure B1 in the Appendix. These results corroborate our finding that sentiment about the future has a larger (and more positive) effect on bank lending in Central Europe.

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. (2023), who found that positive sentiment temporarily increases economic growth. While Constantinides et al. (2023) identify one channel through which sentiment influences economic growth (i.e., by lowering local cost of equity), our results indicate that sentiment can influence real economy through another channel, the bank lending channel. Our results also indicate that housing loans respond to sentiment shocks more strongly than consumer loans. Two potential interpretations underline this channel. First, housing loans are generally larger and have a longer maturity. Therefore, consumers are likely

[7] A positive value of this relative future sentiment indicates that consumers are more positive about the future than about the present.

more cautious when deciding about their demand for housing loans and, thus, positive sentiment (particularly about the future) plays an important role in influencing the decision about the housing loan demand. Second, positive sentiment might lead to higher asset prices, including house prices (Khan et al., 2019), which then increases demand for housing loans (Soo, 2018).

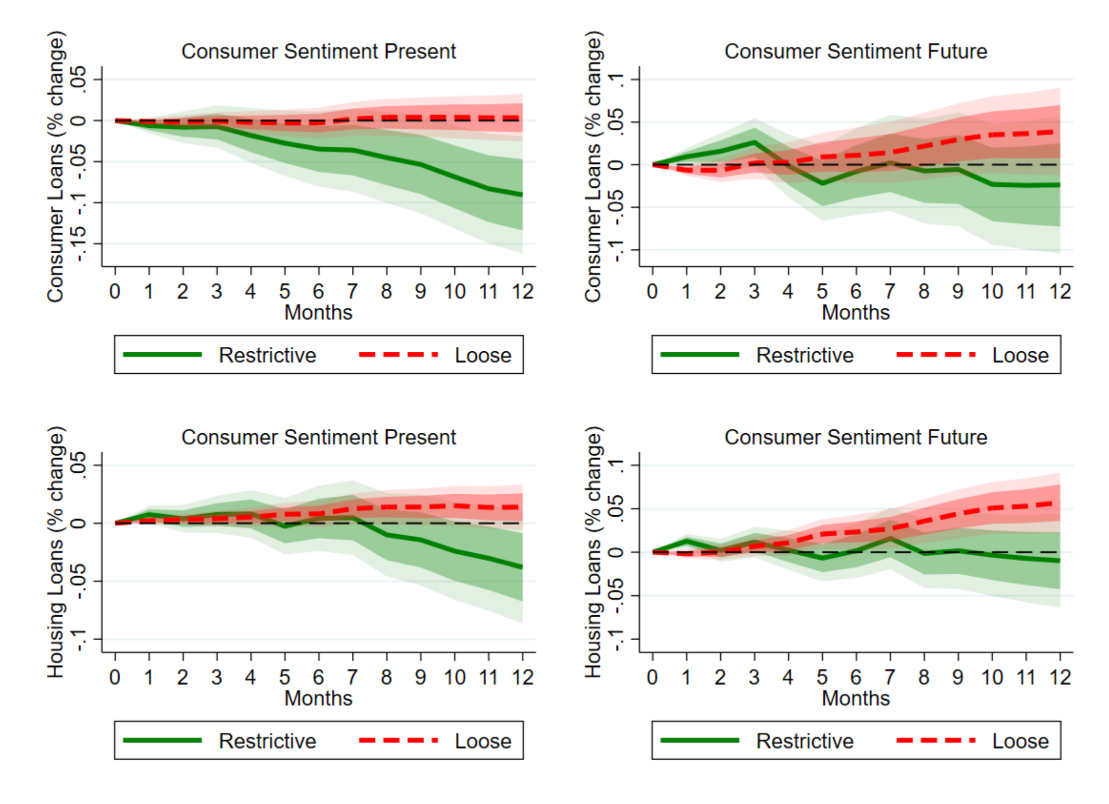
Before proceeding to explore the country-level heterogeneity in the effect of sentiment on bank lending, we exploit the panel structure of our data to identify some factors that might influence the effect of sentiment on bank lending. Considering the importance of monetary policy as the determinant of bank lending and the interaction between monetary policy and sentiment that has already been highlighted by empirical literature (Kashyap and Stein, 2023), we explore whether monetary policy stance affects the effect of sentiment on bank lending.

Figure 4 shows the impulse responses of bank lending to pure sentiment shocks when monetary policy stance is persistently tight or persistently loose. Positive sentiment shocks seem to have a positive effect on bank loans only when monetary policy stance is persistently loose. This positive effect can be observed for both consumer and housing loans, with this effect being larger in magnitude for housing loans. Conversely, when monetary policy stance is persistently tight, the positive effect of pure sentiment shocks disappears:[8] An increase in sentiment about the future that is not driven by improving economic fundamentals affects neither consumer nor housing loans. Initially, present sentiment also has no effect on bank lending. However, after a few months, a positive shock to present sentiment decreases both consumer and housing loans.

The difference between impulse responses to sentiment shocks under contractionary and expansionary monetary policy shown in Figure 4 is also statistically significant in most cases (particularly towards the end of the forecast horizon). Therefore, we conclude that tighter monetary policy limits the transmission of sentiment shocks to bank lending. Namely, while positive sentiment is associated with higher risk-taking (Cubillas et al., 2021), tighter monetary policy limits risk-taking behaviour (Bauer et al., 2023; Kashyap and Stein, 2023). Thus, an increase in sentiment that occurs during periods with restrictive monetary policy might have limited effect bank lending – since higher sentiment would not lead to more risk-taking. Conversely, when the monetary policy stance is expansionary, positive consumer sentiment shock might stimulate more risk-taking behaviour, thus leading to higher loan demand. Similarly, when monetary

[8] The vector of control variables includes central bank interest rate. Thus, the impulse responses in Figure 4 should not be driven by the effect of monetary policy stance on bank lending but should instead reflect heterogeneous responses of bank lending to sentiment shocks under different monetary policy stances.

Figure 4: Effect of Pure Sentiment on Bank Lending – Role of Monetary Policy Stance



Notes: Cumulative IRFs of bank lending to pure sentiment shocks. The solid (dashed) lines represent the responses of bank lending to sentiment when 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 point estimate, shaded areas correspond to 68 and 90 percent confidence bands. The point estimates are the coefficients β^h_{1r} and β^h_{1e} from equation 8 over the entire forecast horizon $h = 1, \ldots, 12$. Month 1 ($h = 1$) is the first month after the sentiment shock. The standard errors used to calculate these confidence bands were clustered at a country level. Y-axis: deviation in percentage points. X-axis: time in months.

policy is expansionary and liquidity is abundant, banks are 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).

4.2.1 Country Specific Heterogeneity

While the results reported in the previous sub-section enable us to make generalized conclusions about the panel of 4 CE economies, the panel framework might mask important heterogeneities across the CE countries. Furthermore, the limited number of countries in our panel might constrain our ability to make generalized conclusions. Therefore, we re-estimate our baseline regressions for each country in our sample separately. We report the country-level IRFs in Figures B2 and B3 in the Appendix.

These findings do indicate significant heterogeneities between the 4 CE countries. Nevertheless, some common patterns can still be observed, which are in line with the panel results: Future sentiment has a more positive effect on bank lending than present sentiment, and housing loans respond more positively to sentiment shocks than consumer loans. For several countries in our sample (Czech Republic, Poland, Slovakia) we observe a negative effect of positive sentiment on bank lending, which is statistically significant in some cases. This negative effect turns larger over time. There are several possible explanations for this puzzling finding: First, as consumers might use consumer loans for consumption smoothing, once their sentiment turns more positive, they might come to expect higher income and thus might opt to rely less on rather expensive consumer loans for consumption smoothing, reducing demand for consumer loans. Second, positive sentiment not explained by fundamental factors might lead to a provision of excess loans that could be corrected later on. That is, positive sentiment might initially prevent loan demand from falling once economic fundamentals start to deteriorate, which is then followed by a correction few months later. In line with this argument, Lopez-Salido et al. (2017) find evidence that exuberant credit market sentiment is followed by a decline in real economic activity in subsequent years, which is driven by re-pricing of credit risk. That is, credit spreads widen on riskier loans, which include consumer loans, reducing the demand for such loans. Third, a positive sentiment not driven by economic fundamentals could be associated with expectations of higher interest rates, which reduces the demand for rather more short-term consumer loans. Fourth, banks might constrain their loan supply when sentiment and its volatility changes Caglayan and Xu (2016). Conversely, in Hungary, positive present sentiment does not have a statistically significant effect on consumer loans while positive future sentiment increases consumer loans. However, we treat the results for Hungary with some caution, owing to Hungary's experience with a larger share of foreign currency-denominated loans prior to 2015.

For housing loans, we find negative effect of positive sentiment in the case of Hungary, no effect in the case of Slovakia, positive effect in the case of Poland. For the Czech Republic, present sentiment appears to have a negative effect while future sentiment has a mildly positive effect on housing loans.

5 Conclusions

In this paper, we study the effect of consumer sentiment on bank lending in 4 Central European economies (Czech Republic, Hungary, Poland, Slovakia), which have experienced significant credit expansion over the past three decades. To identify the effect of sentiment on bank lending, we use an index of consumer sentiment derived from a survey of consumers and we apply machine learning techniques to decompose this sentiment index into the component driven by economic fundamentals (fundamental-driven or news-based) and the sentiment component that is orthogonal to economic fundamentals, or pure sentiment. We use the latter component as a proxy for sentiment shocks and we apply the local projections approach to construct impulse responses of bank lending to these sentiment shocks for the panel of Central European economies, as well as for each country separately. Moreover, we contribute to the literature by distinguishing between shocks to present and to future sentiment.

Our findings can be summarized as follows: Positive sentiment shocks increase housing loans, while they have limited effect on consumer loans. Shocks to future sentiment have a larger effect on bank lending than shocks to present sentiment. The effect of sentiment shocks on bank lending is larger when monetary policy is expansionary. Even for the group of relatively homogenous Central European economies, substantial heterogeneity can be observed in the effect of sentiment on bank lending.

We contribute to 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 open to making major long-term investments, leading to higher demand for housing loans. Nevertheless, demand for consumer loans, which are generally smaller in magnitude and have shorter maturity, does not seem to increase following 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.

Our results also entail some policy implications. Prior research has already concluded 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 expansionary monetary policy creates favourable conditions – potentially by making liquidity abundant and by stimulating risk-taking. Thus, expansionary monetary policy might also stimulate aggregate demand through the bank lending channel by improving sentiment, which then contributes to higher demand for loans. However, there is a potential trade-off for monetary policy: If positive sentiment is not associated with improving fundamentals, persistently expansionary monetary policy might contribute to excessive risk-taking when sentiment is positive, which might lead to unsustainable increase in bank lending, creation of asset price bubbles and, thus, increase the likelihood of financial instability (Ferguson et al., 2023; Grimm et al., 2023).

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Appendices

Appendix A: Consumer Survey Questions

Table A1: Consumer Confidence Index for the Present

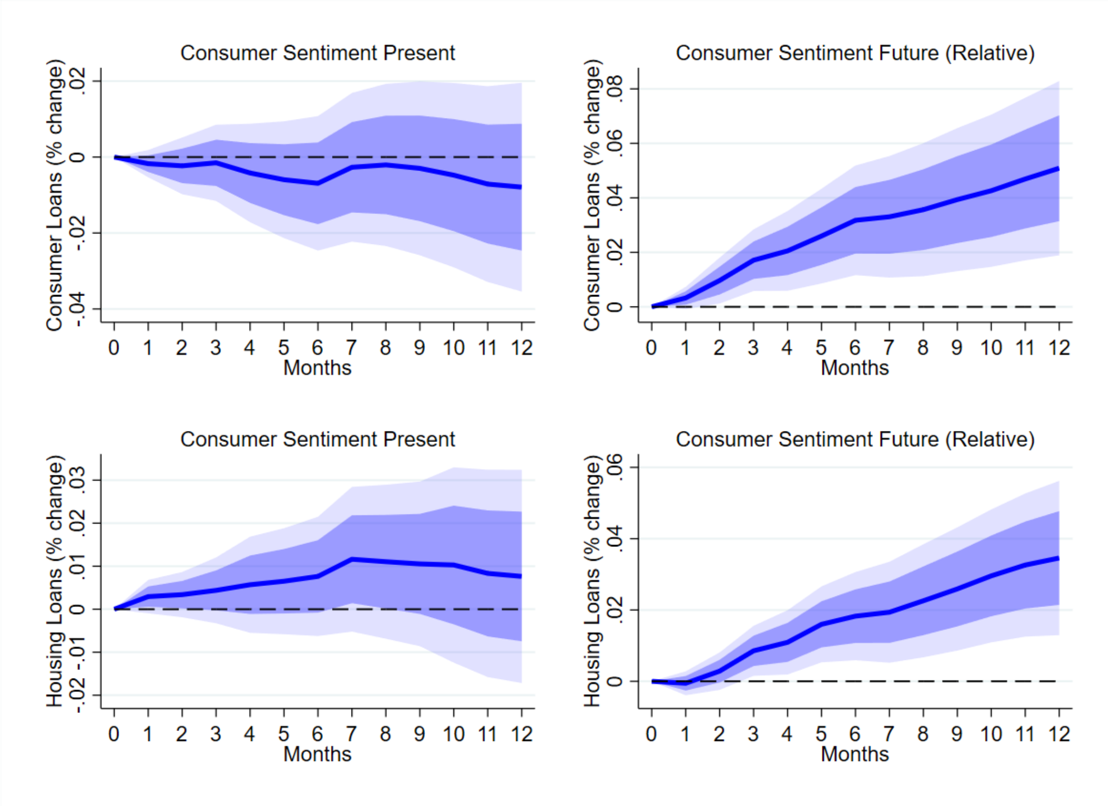
Question	**Answer**
How has the financial situation of your household changed over the last 12 months?	++ got a lot better, + got a little better, = stayed the same, − got a little worse, −− got a lot worse, N don't know
How do you think the general economic situation in the country has changed over 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

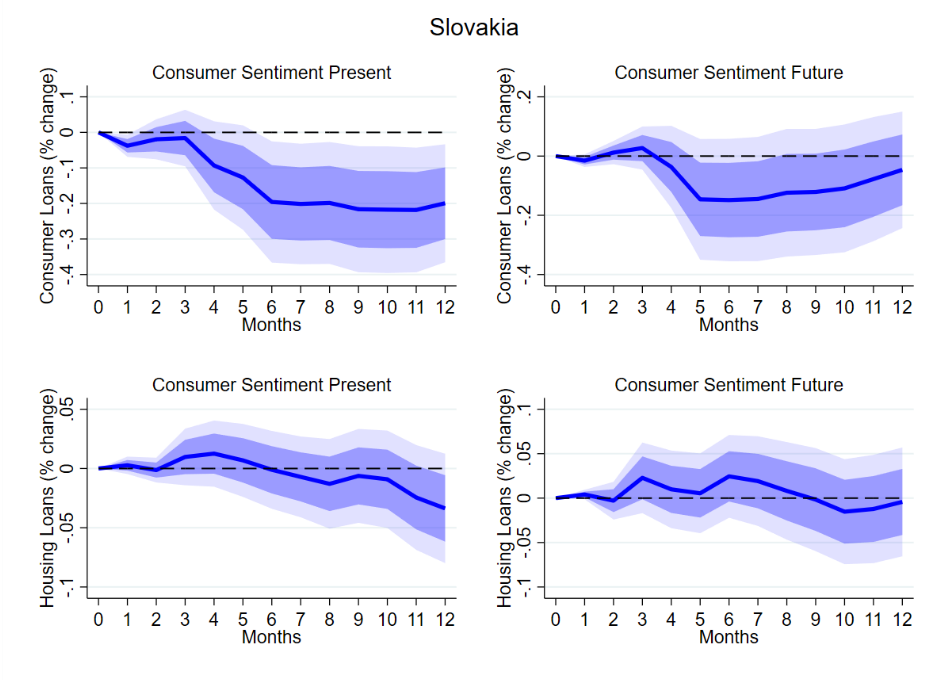
Appendix B: Additional Results

Figure B1: Effect of Pure Sentiment on Bank Lending – Relative Future Sentiment

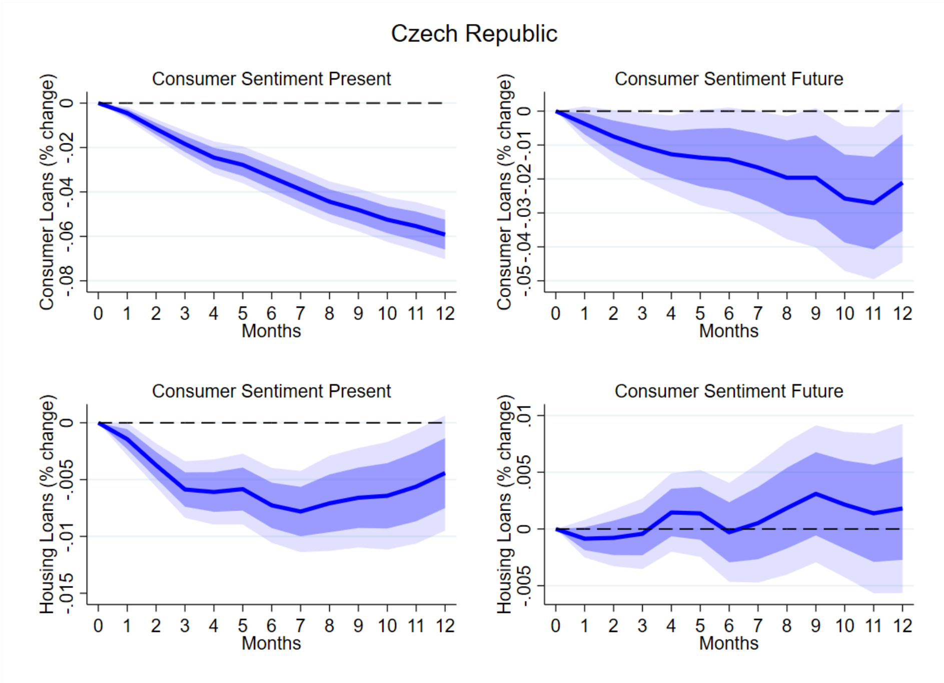


Notes: Cumulative IRFs of bank lending to pure sentiment shocks. The top panel displays the responses of consumer loans, while the bottom panel shows the responses of housing loans. The left panel displays the responses to shocks to present sentiment and these responses correspond to the left panel of Figure 3. The right panel displays the responses to shocks to relative future sentiment. *Relative future sentiment* is calculated as the difference between the sentiment about the future and the sentiment about the present. The solid line represents point estimate, shaded areas correspond to 68 and 90 percent confidence bands. The point estimates are the coefficients β_1^h from equation 5 over the entire forecast horizon $h = 1, \ldots, 12$. Month 1 ($h = 1$) is the first month after the sentiment shock. The standard errors used to calculate these confidence bands were clustered at a country level. Y-axis: deviation in percentage points. X-axis: time in months.

Figure B2: Effect of Pure Sentiment on Bank Lending – Slovakia and Czech Republic

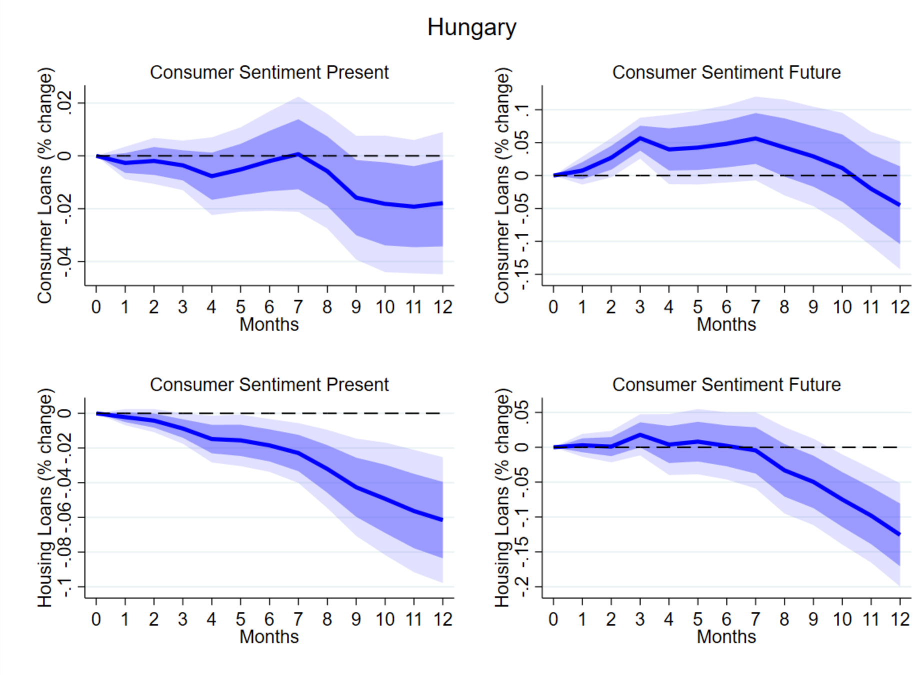


Notes: Cumulative IRFs of bank lending to pure sentiment shocks in the case of Slovakia. The top panel displays the responses of consumer loans, while the bottom panel shows the responses of housing loans. The left panel displays the responses to shocks to present sentiment, while the right panel displays the responses to shocks to future sentiment. The solid line represents point estimate, shaded areas correspond to 68 and 90 percent confidence bands. The point estimates are the coefficients β_1^h from equation 6 over the entire forecast horizon $h = 1, \ldots, 12$. Month 1 ($h = 1$) is the first month after the sentiment shock. Y-axis: deviation in percentage points. X-axis: time in months.

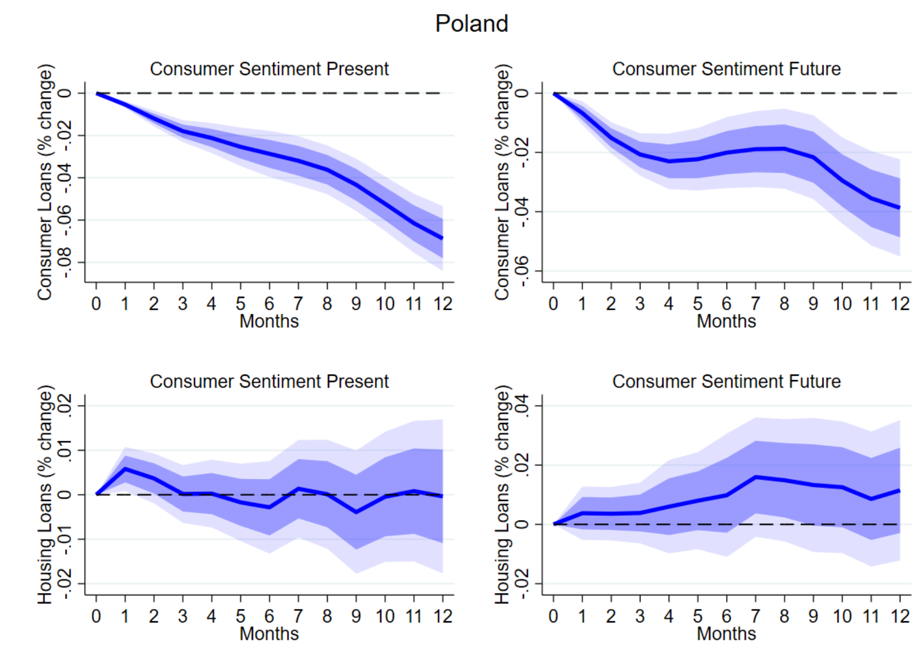


Notes: Cumulative IRFs of bank lending to pure sentiment shocks in the case of the Czech Republic. The top panel displays the responses of consumer loans, while the bottom panel shows the responses of housing loans. The left panel displays the responses to shocks to present sentiment, while the right panel displays the responses to shocks to future sentiment. The solid line represents point estimate, shaded areas correspond to 68 and 90 percent confidence bands. The point estimates are the coefficients β_1^h from equation 6 over the entire forecast horizon $h = 1, \ldots, 12$. Month 1 ($h = 1$) is the first month after the sentiment shock. Y-axis: deviation in percentage points. X-axis: time in months.

Figure B3: Effect of Pure Sentiment on Bank Lending – Hungary and Poland



Notes: Cumulative IRFs of bank lending to pure sentiment shocks in the case of Hungary. 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 point estimate, shaded areas correspond to 68 and 90 percent confidence bands. The point estimates are the coefficients β_1^h from equation 6 over the entire forecast horizon $h = 1, \ldots, 12$. Month 1 ($h = 1$) is the first month after the sentiment shock. Y-axis: deviation in percentage points. X-axis: time in months.



Notes: Cumulative IRFs of bank lending to pure sentiment shocks in the case of Poland. 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 point estimate, shaded areas correspond to 68 and 90 percent confidence bands. The point estimates are the coefficients β_1^h from equation 6 over the entire forecast horizon $h = 1, \ldots, 12$. Month 1 ($h = 1$) is the first month after the sentiment shock. Y-axis: deviation in percentage points. X-axis: time in months.