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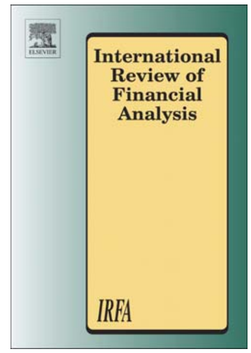

Sentiment volatility and Bank lending behavior

Mustafa Caglayan, Bing Xu

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Sentiment Volatility and Bank Lending Behavior

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Using a panel of commercial, co-operative and savings banks from G7 countries, we investigate whether the changes in sentiment and its volatility affect banks' lending behavior. We show that the changes in economic agents' sentiment and its volatility affect bank lending negatively, while the impact sizes differ across indicators. We also examine volatility effects on banks' loan growth as uncertainty reaches excessive levels. We highlight the role that several bank-specific variables play on bank lending and discuss to what extent uncertainty effects are transmitted on credit growth through them.

Keywords: Bank loans, tier 1 capital, business sentiment, consumer sentiment, leading indicators, uncertainty

JEL classification: C22, C23, D81, E51.

1 Introduction

Although, due to developments in the financial markets, some economists suggest that bank lending may not be as important as it used to be, many argue that banks do play a key role as they specialize in overcoming frictions in the credit market by acquiring costly information on borrowers. To that end, research has shown that reductions in loanable funds could have a major impact on bank-dependent borrowers (e.g., small businesses) and may cause substantial reductions in their fixed investment expenditures or even lead them to bankruptcy (e.g., [10], [31], [26]). Hence, it is not surprising that researchers have begun to examine the factors that affect banks' lending behavior with a renewed attention following the 2008 financial crisis, as the repercussions of this crisis affected many developed and emerging countries throughout the globe.

In this paper, different from the literature, we investigate the association between economic agents' perception of the state of the economy and banks' lending behavior. Surprisingly, although this question relates to research in behavioral finance and psychology, which argues that human behavior differs significantly in times of uncertainty and fear as opposed to periods of prosperity and tranquility, it has not been investigated before (see, for example, [48] , [2], [29], [28]).[1] To carry out our investigation, rather than examining the impact of specific sentiment measures on bank behavior, we focus on composite sentiment indicators which provide a broad perspective of the economic agents' perception on the economic outlook. In this context, survey-based sentiment indicators are widely considered as a critical component by academics, policy makers and media in the transmission of shocks into the economic activity, as these indicators gauge the state of the economy from the point of view of the economic agents.[2]

In our examination, we use three different indicators including business sentiment, consumer sentiment and composite leading indicators which capture the aggregate perception of the business leaders and consumers on the economic outlook. As each type of economic agent acts on a specific set of (imperfect) information that emanates from the state of the economy, rational inattention, or the agent's own asymmetric goals and strategies, it is important to know how bank lending would change in response to variations in sentiment.

An inspection of the level and volatility of the sentiment measures, as displayed in Figure 2, shows that while there are considerable similarities among the series within a country, these series may reach extreme levels.[3,4] In our study, we also identify distinct periods of excessive volatility and examine whether banks' lending behavior changes during these periods. This is important because during such periods, bank managers may change their lending process significantly, as unemployment increases, business conditions worsen and public trust on the policy/decision makers declines ([23]).[5]

While carrying out the analysis, we control for heterogeneous characteristics of the banks' balance-sheet that relate to banks' funding strategy, capitalization, liquidity, loan quality, earning quality and size. As the Basel Accord highlights its importance, we examine the role of high

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[1] Only [23] has examined the lending behavior of the US banks during periods of anxiety. They measured anxiety based on changes in economic agents' confidence levels.

[2] See, for instance, [19], [14], [39], [6], [4], [23], [20].

[3] Business sentiment indicator is not available for Canada.

[4] From here on, we use uncertainty and volatility interchangeably.

[5] Research in psychology, has shown that negative mood significantly affects individual's decision-making process (e.g., [29], [28]).

quality bank capital on loan growth. Furthermore, our model contains several interaction terms between volatility and bank variables so that we can investigate whether volatility affects bank loans through bank-specific variables which are noted to play an important role in banks' lending behavior. Last, but not the lest, we control for macroeconomic conditions by incorporating the GDP growth rate and the interest rate in our empirical models.

To carry out our investigation, we construct a large panel of commercial, co-operative, and savings banks collected from the Bankscope database for the G7 countries including Canada, France, Germany, Italy, Japan, the UK, and the US. This database provides detailed bank-level information yet the sample size is constrained due to the fact that we seek to examine the role of Core Tier 1 capital on banks' lending. The final dataset that we employ in our analysis is comprised of more than 9,000 banks and retains bank, country and time dimensions. The analysis covers the period between 1999-2014.

Our investigation provides evidence that banks curtail their lending in response to changes in sentiment as well as sentiment volatility. In particular, we find that the impact size of volatility effects is much stronger than the impact size of changes in sentiment, 13% *versus* 1%, respectively. When we consider the effects of excessive volatility, we see that volatility associated with leading indicator and business sentiment causes additional reductions in loan growth. Interestingly, when consumer sentiment volatility reaches excessive levels, although the total effect of volatility on loan growth is still negative, this effect is lower compared to low levels of consumer sentiment volatility. Taken together, our empirical results suggest that banks' lending behavior is affected by agents' expectations.

Our investigation also highlights the role that various bank-specific variables play in transmission of uncertainty on the growth of bank loans. Consistent with the common view, we find that increased volatility leads to a drop in loan growth for banks that carry more problem loans. That is banks with bad loan portfolios curb their lending more rigorously in periods of turmoil as they are more exposed to credit risk. We also find that although banks which experience low returns on assets expand their loan growth faster, it is the high return banks that can continue to expand their loans in periods of high volatility. Regarding the bank size, our results show that smaller banks are more aggressive in extending their customer base and seizing new lending opportunities, especially when excessive uncertainty were to arise from the leading indicators. Last, as expected, we find that high quality of bank funding strategy (i.e., Tier 1 bank capital) and liquidity are both crucial for credit growth. However, these two variables do not mitigate the adverse impact of uncertainty on banks' lending behavior.

The paper is organized as follows. Section 2 discusses the related literature. Section 3 presents our formal empirical model. Section 4 discusses the data and the uncertainty measures. Section 5 reports the empirical results as well as the robustness checks. Section 6 concludes the paper.

2 Related Literature

There is a deepening literature on bank lending behavior, as banks play a vital role in a country's economic development and growth. In particular, following the 2008 financial crisis, several researchers have begun to examine the interrelations between risk and bank lending behavior. For example, [3] found that banks with lower expected default frequency were able to offer a larger amount of credit and protect their loan supply from changes in monetary policy. [23] examined the lending behavior of US banks during periods of anxiety. They defined periods of anxiety from the perspective of consumers, firms and market analysts, according to their perceptions and expectations on future economic conditions. Their empirical results showed that when consumers' and analysts' anxiety increase, banks' total loans decline, and that this effect is more pronounced when banks hold a higher level of credit risk, and in periods of anxiety that were followed by recessions. [35] used a cross-country bank panel to test whether the quality of bank capital mattered for loan growth during the 2008 financial crisis. They found that the availability of high quality funds (tier 1 capital and retail deposits) and government support were crucial in continuous bank lending during periods of crisis.

Another strand of literature has focused on the role of bank ownership on banks' cyclical lending behavior over the business cycle. This literature provides mixed findings on the importance of ownership in times of crises. [30] found no difference in the cyclical pattern of lending between government-owned and private banks. [21] showed that state banks in Latin America lend counter-cyclically, whereas the state banks in Eastern Europe do not. In contrast, [27], [16] and [15] found evidence that government-owned banks increase their lending during crises relative to normal times, while private banks' lending decreases. Thus, they argued that governments can indirectly play an active counter-cyclical role in financial markets. [26] suggested that, irrespective of the state of the economy or the financial markets, stakeholder banks attempt to smooth financial conditions for their customers to maintain longer term borrower-lender relationship by conducting less procyclical loan supply polices. [11] showed that lending by state banks is less procyclical than lending by private banks, especially if the bank is located in a country with good governance.

When we sift through the literature, we identify a number of studies which examine bank lending behavior during the recent financial crisis using loan-level data. For instance, [41] studied retail banks' lending in Germany and found an overall reduction in demand for consumer loans as well as a significant contraction in the supply of loans following the US financial crisis. According to [31], new lending across all types of loan categories declined substantially during the 2008 financial crisis. They showed that part of this decline could be explained by a drop in demand as firms scaled back their expansion plans, and other part may be attributed to the reduction in the supply of loans, especially for banks with less access to deposits, as well as to banks' desire to curtail their credit-line drawdowns due to increased risks in this period.

In addition, a number of studies examined the impact of macroeconomic uncertainty on the cross-sectional dispersion of bank loans. [9] showed for a large panel of US banks that macroeconomic uncertainty has a negative effect on the cross-sectional dispersion of total-loans-to-assets ratio and argued that uncertainty distorts the efficient allocation of scarce bank resources. They claim that uncertainty affects bank managers ability to predict returns from available lending opportunities and as a consequence act more conservatively while they cut back on loans. Following [9], [43], using a large panel of banks in Italy, and [18], examining the largest 6 banks from Canada and 20 banks from the US, arrived at similar conclusions.

Our paper also relates to the extensive literature on behavioral finance. Survey-based sentiment indicators have long been scrutinized for the information they contain on the state of the economy which is not already covered in other well-used economic indictors. For example, [40] and [7] showed that Michigan's Index of Consumer Sentiment is very useful in forecasting GDP. [19], [14] and [39] suggested that measures of consumer sentiment (i.e., Michigan's Index of Consumer Sentiment and Conference Board Index) contain information about consumers' future spending. This is sensible when we consider the life-cycle hypothesis as it suggests that consumers could spend more today if they were more optimistic about their future income. More recently,

[20] found strong evidence that sentiment variables (i.e., Michigan's Index of Consumer Sentiment and Purchasing Manager's Index) hold significant predictive power in capturing recessions in the US in excess of standard recession predictors and common factors.

Furthermore, there is a large and growing literature which examines the impact of investor sentiment on stock returns. Most studies tend to use a range of survey-based or market-based investor sentiment proxies. [42] examined the close-end fund discount and consumer confidence as alternative measures of sentiment, and found that only the latter played a significant pricing role in the US. [5] constructed a composite investor sentiment index by using the first principal component of six sentiment proxies suggested in prior research and showed that this composite index significantly predicted the future stock returns.[6] [8] examined the relationship between a number of investor sentiment measures and G7 stock market returns. In addition, a number of authors constructed text-based measures of investment sentiment through sources such as media or internet articles. For example, [28] constructed media-based text measures of investor sentiment and found that news content can help one to predict stock returns at the daily frequency, especially during recessions. Recent survey study by [33] compared and contrasted various text-based sentiment measures, and also provided a comprehensive survey on the empirical studies on the impact of sentiment and stock returns, or trading volumes, or firm fundamentals and market efficiency.

In the main, our study contributes to the literature on the determinants of banks' lending behavior in relation to changes in sentiment that emanate from business, consumer, and leading indicators. Focusing our attention on the G7 countries' commercial, co-operative, and savings banks, we examine both the level and volatility effects of business sentiment, consumer sentiment, and the leading economic indicator on banks' lending activities. Next, to examine the asymmetric effects of sentiment volatility, we investigate how credit growth changes during episodes of extreme volatility. Furthermore, we test to what extent volatility affects bank loans through its impact on various bank-specific variables. In our analysis, we control for macroeconomic factors that may effect bank lending behavior.

3 Methodology

In what follows, we first present a nave model where we only allow for bank-level and macroeconomic control variables to explain banks' loan growth. Next, we augment our basic model by introducing the variables that capture the changes in the level and volatility of sentiment. Finally, we examine how credit growth changes during episodes of extreme volatility and to what extent bank-specific variables transmit uncertainty effects on bank lending. Table 1 provides the descriptives of the variables used in our models.

3.1 Basic bank lending model

Our basic model assumes that a bank's ability and propensity to increase its loan supply depend both on its own characteristics and on the environment within which it operates:

$$\Delta ln(loans_{i,t}) = \alpha + \boldsymbol{\gamma}\mathbf{X_{i,t-1}} + \phi\mathbf{MacroControl_{j,t-1}} + \nu_i + year_t + \varepsilon_{i,t} \quad (1)$$

The dependent variable, $\Delta ln(loans)$, captures the loan growth of bank i at time t; $\mathbf{X}$ is a vector

[6] They used close-end fund discount, market turnover, number of IPOs, average first day return on IPOs, equity share of new issuances, and log difference in book-to-market ratios between dividend payers and dividend non-payers.

of bank-level explanatory variables that captures bank characteristics; $\mathbf{MacroControl}$ is a vector of macroeconomic control variables for country; ν_i captures bank fixed effects, $year_t$ denote year dummies, and $\varepsilon_{i,t}$ is the error term.

For robustness purposes, we carry out the analysis for changes in net-loan growth (Δln_NL) and that in gross-loan growth (Δln_GL). As explanatory variables, the model embodies five bank-level variables that earlier research has shown to play an important role in determination of loan supply. Firstly, we should stress that our model incorporates a variable that captures the role that high quality funding sources play. Although, in line with the Basel Accords, researchers generally employ equity-to-total-asset ratio to account for banks' solvency, we use Tier 1 regulatory capital ratio, ($Tier1$), in our model,[7] as a broader measure of regulatory capital.[8] This measure, has the highest loss-absorbtion capacity, and we expect to find that Tier 1 capital will have a positive effect on credit growth ([35]).

Our second variable captures the quality of banks' loan portfolio as we measure the extent of total loans that are impaired or doubtful ($Impaired\_GL$). This variable is shown to play an important role in bank managers' lending decisions, especially during periods of uncertainty (e.g., [17], [23]). To that end, if a bank holds a relatively risky portfolio, then the bank managers might behave more conservatively in issuing new loans, while other banks might have the latitude to lend more if their portfolios are less risky. Hence, we expect a negative relationship between the level of bad loans and loan growth. Furthermore, we use the natural logarithm of bank's total assets ($Size$) as a proxy to measure the effect of bank size on loan growth. We predict a negative sign here, as smaller banks tend to expand loans more aggressively (e.g., [23], [11]).

Our model also contains return on average assets ($ROAA$) as a proxy to reflect banks' earning quality, efficiency and operational performance. We expect that $ROAA$ will have a negative impact on changes in bank loans for more profitable banks should have a more rigorous reviewing process and less interest in increasing 'marginal' and lower quality lending ([47]). Lastly, we incorporate a measure of bank liquidity in our model, a variable which is often considered to have an important influence on banks' lending behavior (e.g., [32], [26]). We use the ratio of liquid assets on total customer deposits and other short-term borrowing ($Liquid\_Tdb$) as a proxy to gauge banks' liquidity.[9] We predict that more liquid banks will be able to lend more as compared to illiquid banks.

Each model also contains two macroeconomic control variables (extracted from the Datastream): GDP growth rate (ΔGDP) and the long-term interest rates (IR).[10] We expect that GDP growth will have a positive impact on loan growth whereas interest rates will have a negative impact.

3.2 Bank loans and the level and volatility effect of sentiment

Given that the perception of economic agents' views are captured by different type of sentiment indicators, we examine the impact of business sentiment, consumer sentiment and the leading indicator on banks' lending behavior.[11] Using these indicators, we examine to what extent

[7] Under Basel III, there is a narrower definition of Tier 1 regulatory capital. For example, common equity (e.g., retained earnings, share premium reserves) will continue to qualify as core Tier 1 capital, but other hybrid capital instruments will be replaced by instruments that are more loss-absorbing.

[8] See for example, [22], [23] who argued that well-capitalized banks can better protect their lending from monetary policy shocks.

[9] Liquid assets include cash, government bonds, short-term claims on other banks (including certificates of deposit).

[10] Long-term interest rates refer to government bonds with a residual maturity of about ten years.

[11] It is widely acknowledged that sentiment plays an important role in the transmission of shocks on the economy (e.g., [6], [4], [23]).

changes and the volatility of sentiment that emanate from any of these sources affect bank lending. To do so, we modify our basic model as follows:

$$\Delta ln(loans_{i,t}) = \alpha + \boldsymbol{\gamma}\mathbf{X}_{\mathbf{i,t-1}} + \boldsymbol{\lambda}\boldsymbol{\Delta}\mathbf{Sent}_{\mathbf{j,t-1}} + \boldsymbol{\beta}\boldsymbol{\hat{\sigma}}_{\mathbf{Sent}_{\mathbf{j,t-1}}} + \boldsymbol{\delta}(\boldsymbol{\hat{\sigma}}_{\mathbf{Sent}_{\mathbf{j,t-1}}} \times \mathbf{X}_{\mathbf{i,t-1}})$$
$$+\phi\mathbf{MacroControl}_{\mathbf{j,t-1}} + \nu_i + year_t + \varepsilon_{it} \tag{2}$$

where $\boldsymbol{\Delta}\mathbf{Sent}_{\mathbf{j}}$ and $\boldsymbol{\hat{\sigma}}_{\mathbf{Sent}_{\mathbf{j}}}$ denote vectors of changes in sentiment and volatilities of sentiment which emanate from the aforementioned sources, respectively.

In Equation (2), the sign of the coefficient associated with changes in sentiment is ambiguous as it could take a positive or a negative sign, depending on how bank managers perceive the state of the economy. For example, bank managers may see positive changes in sentiment as a signal that the economy is overheating and predict that the monetary policy authorities could raise interest rates in anticipation of higher inflation in the future. In such circumstances, bank managers would be reluctant to extend credit due to balance sheet effects that may emerge in the future. In contrast, if bank managers predict that the economy will continue to expand without the interference of the monetary policy authorities, then a positive change in sentiment indicators may initiate a new round of lending. Hence, we let the data to determine the sign of the coefficient associated with changes in sentiment.

In contrast, we expect that sentiment volatility will exert a negative impact on credit growth, although the impact size should vary across different sentiment measures. One can reasonably argue that in periods of expansion, business leaders and consumers feel happy and optimistic, whereas during volatility, they feel fearful and anxious due to job losses, demand declines and uncertainty over the future (e.g., [48], [29]). Sentiment volatility captures variations in economic agents' expectations about the future economic outcomes. In particular, during periods of uncertainty, as [9] argue, bank managers are expected to behave more conservatively in issuing new loans, as they cannot accurately evaluate the expected returns from lending. In such circumstances, as both households and businesses are more prone to bankruptcy, bank lending declines.

We measure sentiment volatility by the conditional variance obtained from ARCH/GARCH specifications, as detailed in Section 4.2. The expanded model also contains a vector of double interaction terms ($\boldsymbol{\hat{\sigma}}_{\mathbf{Sent}} \times \mathbf{X}$) between the volatility and bank-level variables. These interaction terms will allow us to examine to what extent volatility effects transmit on bank lending through bank-level variables which are shown to affect bank lending behavior in the literature.

3.3 Effects of excessive volatility on credit growth

So far, we have hypothesized that credit growth responds proportionately to changes in sentiment volatility. However, during periods of excessive volatility, banks' lending behavior may differ significantly, as adverse selection and moral hazard problems intensify (see for example, [44], [45], [23]). To consider the possibility of an asymmetric transmission of sentiment volatility on banks' credit growth, we extend our earlier model by incorporating an interaction term that captures the effects of extreme volatility. In line with the standard approach, to capture asymmetric volatility effects, we create the following dummy variable:

$$\hat{\sigma}^{Asy}_{Sent_{j,t}} = \begin{cases} 1 & \text{if} \hat{\sigma}_{\mathrm{Sent}_{\mathrm{j,t}}} \geq 70 \text{Percentileof} \hat{\sigma}_{\mathrm{Sent}_{\mathrm{j}}} \\ 0 & \text{Otherwise} \end{cases}$$

Using this rule for each volatility measure in each G7 country, we set the dummy to 1 when $\hat{\sigma}_{Sent}$

exceeds its 70th percentile or zero otherwise. Next, we interact the high volatility dummy, $\hat{\sigma}_{Sent}^{Asy}$, with bank-level and volatility variables to examine the impact of high volatility on banks' loan growth. The model takes the following form:

$$\Delta ln(loans_{i,t}) = \alpha + \boldsymbol{\gamma}_{\mathbf{i}}\mathbf{X}_{\mathbf{i,t-1}} + \boldsymbol{\lambda}\mathbf{\Delta Sent}_{\mathbf{j,t-1}} + \boldsymbol{\beta}\hat{\boldsymbol{\sigma}}_{\mathbf{Sent}_{\mathbf{j,t-1}}} + \boldsymbol{\theta}(\hat{\boldsymbol{\sigma}}_{\mathbf{Sent}_{\mathbf{j,t-1}}} \times \hat{\boldsymbol{\sigma}}^{\mathbf{Asy}}_{\mathbf{Sent}_{\mathbf{j,t-1}}})$$
$$+\boldsymbol{\delta}(\hat{\boldsymbol{\sigma}}_{\mathbf{Sent}_{\mathbf{j,t-1}}} \times \mathbf{X}_{\mathbf{i,t-1}}) + \boldsymbol{\rho}(\hat{\boldsymbol{\sigma}}_{\mathbf{Sent}_{\mathbf{j,t-1}}} \times \hat{\boldsymbol{\sigma}}^{\mathbf{Asy}}_{\mathbf{Sent}_{\mathbf{j,t-1}}} \times \mathbf{X}_{\mathbf{i,t-1}})$$
$$+\phi\mathbf{MacroControl}_{\mathbf{j,t-1}} + \nu_i + year_t + \varepsilon_{it} \tag{3}$$

where the double interaction term, $\hat{\boldsymbol{\sigma}}_{\mathbf{Sent}} \times \hat{\boldsymbol{\sigma}}^{\mathbf{Asy}}_{\mathbf{Sent}}$, allows us to examine the impact of excessive volatility effects on credit growth and the triple interaction term, $\hat{\boldsymbol{\sigma}}_{\mathbf{Sent}} \times \hat{\boldsymbol{\sigma}}^{\mathbf{Asy}}_{\mathbf{Sent}} \times \mathbf{X}_{\mathbf{i}}$, captures to what extent excessive volatility effects are transmitted on credit growth through bank-specific variables.

We implement two approaches to estimate the basic model. First, we use the fixed effect (FE) model with robust standard errors and include year dummies to control for the changes in unobservable annual shocks that may effect bank loans. Second, we use the two-step difference generalized method of moments (GMM) approach and employ a cluster-robust estimator (where clusters are defined by banks) to account for within-cluster correlation of the disturbances. Given that the use of these two regression methods have led to similar results and that the magnitude of the lagged dependent variable was small, in what follows, we present fixed effects results only.[12]

4 Data

Our study spans the period between 1999-2014 and includes commercial, co-operative and savings banks in G7 countries: Canada, France, Germany, Italy, Japan, the UK, and the US. We extract bank-level data from BvD Bankscope. We primarily use unconsolidated statements when available in Bankscope, otherwise, we use consolidated statements (e.g., [38]).

To remove the impact of outliers, after constructing the net-loans-to-total-assets (NLTA) ratio, we trim the top and lower 5 percentile of this variable. As a consequence, we identify 9,317 banks for which we have information on all variables, including the Tier 1 capital ratio for the time period and countries covered by our study.

Table 2 provides the basic information on our bank data for each country and for G7. Panel A provides the number of banks, as well as the mean and the standard deviation of NLTA and the gross-loans-to-total-assets ratio (GLTA). It should be noted that while some of the countries contribute as many as 7,109 banks (US), some others contribute as few as 40 banks (Canada (41), France (36) and UK (49)). Although this seemingly large variation in bank numbers across countries may be worrying, the average net-loans-to-total-assets ratios, μ_{NL}, which mostly range between 40% to 60%, happen to be similar across all countries.[13] Similarly, the average standard deviation of NLTA ratios, σ_{NL}, across countries is around 20%. The lowest average standard deviation of NLTA ratio is observed in Japan (13%) and the highest value is observed in Canada (22%). We observe a similar pattern for the average and standard deviation of GLTA ratios.

Panel B reports the descriptive statistics for the bank-specific variables that we use in our models. The average gross loan growth (Δln_GL) or net loan growth (Δln_NL) is about 7.8% for

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[12] We estimated the remaining models using GMM as well. The coefficient estimates from this exercise were similar to those obtained under the fixed effects models, but the Hansen J test was generally failing. This failure is mainly due to the increases in the explanatory variables that we had to incorporate in the model, which, as a consequence, have lead to a substantial increase in the number of instruments. Hence, we do not report these results.

[13] France stands at the lowest end (44%) and Italy stands at the highest end (66%).

G7 countries. We also see that the standard deviation of loan growth for both types of loan definitions is around 22%. When we look at the individual country level data, we find that Canada has the highest average loan growth (over 11%) but its standard deviation is much higher than other countries (over 39%), while Japan has the lowest loan growth with just over 2.4%. The average Tier 1 ratio is 17.169%; and Canada stands at the highest end (19.5%), while Japan is at the lowest end (8.73%). Furthermore, the average value of impaired loan to gross loan ratio is 1.996%. Canada and US tend to have better quality loans whereas banks in Italy appear to suffer the most on this account. US banks have the lowest average size among the G7 countries.[14] The average banks' liquidity ratio is 11.86%, and this ratio varies substantially among the G7 countries as it ranges between 8.74% to 35.56%. Finally, the average profitability is around 0.74%. Banks in Canada have the highest return (1.3%) while Japanese banks only have an average return on assets about 0.022%. These key ratios seem to suggest that banks in Canada are more resilient than those in other countries against crises.[15]

Panel C includes the mean and standard deviation for the two macroeconomic variables, (ΔGDP and IR), which allows us to control for the demand-side effects on loan growth. The average value for ΔGDP is 1.89% and IR is 4.47%, yet these figures vary across countries.

Panel D reports the mean and standard deviation of the change (ΔCLI) and volatility ($\hat{\sigma}_{CLI}$) of leading economic indicators, business sentiment indicators (ΔBCI and $\hat{\sigma}_{BCI}$, respectively), and consumer sentiment indicators (ΔCCI and $\hat{\sigma}_{CCI}$, respectively). The average value of ΔCLI is 0.042, ΔBCI is 0.055 and ΔCCI is -0.016. The average value of $\hat{\sigma}_{CLI}$ is 0.008, $\hat{\sigma}_{BCI}$ is 2.009% and $\hat{\sigma}_{CCI}$ is 2.269%. These values for both changes and volatilities differ substantially across countries.[16]

Table 3 provides the correlation matrix for all the variables. What we observe is that high quality bank funds (Tier 1) is positively correlated with loan growth whereas the remaining variables, including sentiment volatility measures, which we discuss below, are negatively correlated. Although these correlations provide an initial impression regarding the impact of each variable on loan growth, given that we are examining data collected from several countries and that each country could be subjected to certain country-specific shocks, a formal empirical investigation should be carried out before acknowledging the effects of these variables on banks' loan growth.

4.1 Sentiment Indicators

When we survey the literature, we come across an expanding research area that examines the effects of sentiment on the behavior of decision-makers, institutions and markets. In their studies, researchers use various sentiment proxies including market-based measures, survey-based measures and text-based measures. In our investigation, we examine the role of general composite survey-based indicators rather than specific sentiment series. This is because composite sentiment measures provide a broader perspective of the economic agents' perception on the state of the economy rather than on specific issues which may be of more concern to investor behavior (e.g., trading volume, mutual fund flow, closed-end fund discount, average first-day IPO returns). In

[14] This should not be too surprising. While there are very large banks in the US, the majority of the banks are small.
[15] During the 2008 financial crisis, several high-profile banks in Europe and the US collapsed, while others some were bailed out, or taken-over. However, to our knowledge, Canada's banking system performed much better and not one Canadian bank failed or openly bailed out.
[16] BCI index for Canada is not available.

fact, several studies have found strong evidence that survey-based composite sentiment indicators hold significant predictive power in macroeconomic variables such as GDP, consumer spending, recessions and stock market returns, in excess of other well-used standard predictors.[17]

In this study, we extract standardized and amplitude adjusted business confidence indicators, consumer confidence indicators, and composite leading indicators for Canada, France, Germany, Italy, Japan, the UK, and the US from the Organisation for Economic Cooperation and Development (OECD) *iLibrary*.[18] These series are available under the OECD monthly main economic indicators.[19] Note that the main advantage of obtaining these composite indicators from OECD is that OECD applies the same criteria to construct these indicators across countries so that they are consistent and comparable across all G7 countries.

We use the Business Confidence Index (BCI) as a proxy for managers' sentiment, as this indicator combines a set of business tendency survey variables (e.g., the current and immediate future expectations on production, orders and stocks) into a single composite sentiment indicator that summarizes managers' assessment and expectation of the general economic situation.[20] To capture consumer sentiment, we make use of Consumer Confidence Index (CCI). Similar to BCI, CCI is based on information collected from consumer opinion surveys regarding the households' intensions for major purchases, their current economic state as compared to the recent past and their expectations for the immediate future (i.e., 3 months). The main characteristic of these surveys is that instead of asking for exact figures, they usually ask for the direction of change by referencing to a "normal" state.[21] In translating these qualitative results into a time series, only the balance is shown by taking the difference between percentages of respondents giving favourable and unfavourable answers. Both BCI and CCI are expressed as an index (long-term average = 100) and they are seasonally adjusted.

Last, we use the amplitude adjusted Composite Leading Indicator (CLI) as our third sentiment variable. CLI is an aggregate time series which comprises a set of component series selected from a wide range of key short-term economic indicators. Although the underlying component series can be different for different countries depending on their economic significance, cyclical behavior, data quality, timeliness and availability for the specific country, the CLI is designed to capture turning points and moves in the same directions as the business cycle.[22]

4.2 Generating a measure of sentiment volatility

To examine volatility effects of sentiment on banks' loan growth, we fit an ARCH/GARCH model on the log difference of the business confidence (ΔBCI), consumer confidence (ΔCCI), and composite leading (ΔCLI) indicators over the period between

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[17] See for example, [19], [40], [7], [39]; [42], [8]; [20].

[18] OECD *iLibrary* is the online library of the OECD featuring its books, papers and statistics and is the gateway to OECDâ€™s analysis and data. However, OECD does not provide business confidence indicator for Canada, see http://www.oecd-ilibrary.org/economics/data/main-economic-indicators_mei-data-en.

[19] Detailed description can be found at https://data.oecd.org/leadind/consumer-confidence-index-cci.htm.

[20] For a detailed explanation on how BCIs are computed, the reader is referred to *"Business Tendency Surveys: A Handbook"* at http://www.oecd.org/std/leading-indicators/31837055.pdf.

[21] OECD generally uses the three-point scale for possible answers (e.g., above normal, normal, or below normal) for business surveys; and uses five-point scale (e.g., increase sharply, increase slightly, remain the same, fall slightly, or fall sharply) for consumer surveys.

[22] For example, the component series used to construct the CLI for the US are: the number of dwellings started, net new orders for durable goods, the NYSE composite share prices, consumer sentiment indicator, weekly manufacturing hours of work, purchasing managers index and the spread of interest rates. For the UK, the component series are business climate indicator, new car registrations, consumer confidence indicator, Sterling 3 months interbank lending rate, production: future tendency, finished goods stocks and the FTSE-100 share price index.

1980–2014.[23] We should note that prior to estimating the model, we tested and confirmed the presence of ARCH effects using the Lagrange Multiplier (LM) test. The GARCH(p,q) model takes the following form:

$$s_t = \alpha + \Sigma_k^r \gamma_k s_{t-k} + \varsigma_i i.month + \varepsilon_t \tag{4}$$

$$\hat{\sigma}_{Sent_t} = \omega_0 + \Sigma_k^q \omega_k h_{t-k} + \Sigma_k^p \omega_k \varepsilon_{t-k}^2$$

where s_t denotes log difference of BCI, CCI, or CLI, $i.month$ captures month effects, $\varepsilon_t = \mu_t \sqrt{\hat{\sigma}_{Sent_t}}$ and μ_t is a zero mean, unit variance white noise process.

We estimate a variant of the above model by fitting an ARCH(p) or GARCH(p,q) model for each country and the sentiment measure. For all countries, we used a low order GARCH(p,q) model with the exception of Japan's leading indicator volatility where a simple ARCH(2) model was preferred.[24] In all cases, we examine the standardized residuals. Ascertaining that the selected model is well specified, we take the within year average of the estimated conditional variances to match the frequency of the bank-level data. The series, which we denote as $\hat{\sigma}_{Sent}$ in equations 2 and 3, are then interpreted as a measure of volatility for the future economic outcomes as perceived by economic agents.[25] Here, higher levels of conditional variance imply higher uncertainty for the future economic outcomes. Table 2 Panel D provides the average and standard deviation of sentiment volatility for each country, $\hat{\sigma}_{Sent}$, that we observe in the data.

5 Empirical Findings

This section presents our findings on bank loans growth with respect to the bank characteristics, the level and volatility of sentiment and macroeconomic control variables. All models allow for country-specific and year fixed effects and all tables report robust standard errors.

5.1 Basic bank lending model results

Table 3 reports the results for our basic model for both net-loan growth (the former 2 columns) and gross-loan growth (the latter 2 columns). This model is estimated using both fixed effects and the two-step difference GMM approach. In order to determine the appropriateness of the GMM results, we report the heteroscedasticity-consistent *Hansen J-test* for the validity of the instrument set, and the Arellano-Bond test for the absence of second-order residual autocorrelation (*AR2 test*). Both tests show that the models are well-specified and there is no second-order serial correlation. It should also be noted that the coefficient estimates from both approaches are very similar and that even though the lagged dependent variable is significant its magnitude is small, suggesting little persistence in changes in bank loans.

When we peruse the table, we see that all coefficient estimates take the expected signs. First of all, we observe that high quality bank funding, $Tier1$, has a positive and highly significant impact on the growth of bank loans. This implies that well-capitalized banks are in a better position to absorb shocks and actual credit and liquidity risk exposures, so that they can continue with their lending activities. Such banks, which hold more capital in excess of the minimum requirement to meet prudential regulation standards, adjust their lending less especially during the

[23] ARCH models are estimated for a longer period for each country than the span of the data that we extracted from the Bankscope database, to work with a longer set of data to compute the parameters. Standard references are [25] and [13].
[24] To save space, we do not report the details from these models, but they are available upon request.
[25] Several researchers have implemented a similar approach to examine the uncertainty effects on real economic activities.

economic downturns in order to avoid regulatory capital shortfalls.[26] Secondly, we see that the impaired loans have a negative impact on loan growth. This suggest that banks which write-off significant amounts of bad-credit from their books reduce their loan growth. These findings are consistent with [37], [23] who also found a significant negative relationship between loan growth and loan losses.

We also observe that loan growth is negatively related with bank size. This suggests that smaller banks extend more new loans than their larger counterparts. To that end, [49] suggested that small banks have a comparative advantage in processing soft information and delivering relationship lending. With respect to return on assets, we find negative and highly significant coefficients when we use the fixed effect model, while GMM approach suggests that return on assets does not affect loan growth. One possible interpretation for negative effects of size and return on assets may be that small banks which experience lower returns act more aggressively in extending their customer base by seizing new lending opportunities. According to a standard Cournot model with capacity constraints, smaller banks may have to offer a lower rate than banks with higher capacity to attract customers ([46]). Another possible explanation suggest that larger banks which have better access to markets and experience economies of scale in managing wholesale deposits (e.g., large-denomination certificates of deposit and subordinated debt), could be less interested to attract the marginal retail depositors, and thus offer lower deposit rates than other banks ([47]). Lastly, we find a positive relationship between liquidity and loan growth. This observation confirms earlier research which has shown that banks continue their lending activities if they had better access to deposit financing ([31]).

When we turn to the impact of macroeconomic variables, which capture the demand-side effects, we see that these variables have the correct signs although they do not play a significant role in the model. This may be due to the fact that our models contain year fixed effects, which may be fully absorbing the demand effects.

5.2 The effects of sentiment on bank lending behavior

In this section, we report our findings on the role of sentiment on banks' credit growth. Table 4 lists all the bank variables whose effects we examined in the previous tables as well as the level, volatility and extreme volatility effects of sentiment for each categories, in the order of composite leading indicator (CLI), business sentiment (BCI) and consumer sentiment (CCI) on banks' loan growth.[27] The first column under each sentiment category presents the level and volatility effects, while the next introduces the extreme volatility effects. All models include country and year fixed effects.

Inspecting Table 4, we can see that the impact of bank-level variables is the same as that in Table 3. Therefore, we focus on the level and volatility effects of sentiment. First, we find that for all three categories, change in sentiment has a significantly negative impact on banks' loan growth, except for the model in column 5. In general, positive changes in sentiment measures are typically associated with the heating up of the economy which eventually requires the central bank to take action by increasing the interest rate to stop the buildup of inflationary pressures. Hence, a negative coefficient on sentiment may be explained by the bank mangers' expectations on future interest rate increases in an overheating economy. Overall, these findings are consistent with [23] , who also reported that changes in sentiment affect loan growth negatively.

When we turn to the volatility effects of sentiment, we find that consistent with our

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[26] See [35] for a more detailed discussion on high quality capital.

[27] We suppress the estimated coefficients associated with macroeconomic variables and the constant.

expectations, sentiment volatility always has a negative and significant impact on loan growth regardless of its source. Negative effect of volatility on bank loan growth is sensible because bank managers would behave more conservatively in issuing new loans during periods of volatility. In particular, given that sentiment volatility is driven by expectations about the future economic outcomes, the information embedded in these volatility series would suggest that bank managers cannot accurately predict returns from outstanding projects (e.g., [9]). In such an environment, it would be nave to expect bank managers to expand credit growth for such behavior could lead to more write-offs, as businesses are more prone to bankruptcies during periods of volatility. In extreme cases of volatility, we observe a very significant and negative effect, which further strengthen our view that under higher uncertainty banks' loan growth decline faster. The only counter view to this argument is for the case of excessive consumer sentiment volatility: although banks reduce their overall lending in periods of extreme consumer volatility, this effect is slightly dampened in comparison to low levels of uncertainty.

When we examine the impact size of volatility effects on bank loans we see that it is much stronger than that of the changes in sentiment, (13% *versus* 1%, respectively). Furthermore, we find that the volatility effects emanating from business sentiment has the least impact (around 2%) and that emanating from the consumer sentiment is the highest impact (around 13%), while leading economic indicator uncertainty reduces credit growth by more than 8%. One possible reason as to why consumer sentiment volatility affects bank credit growth more than the other two is the fact that aggregate consumption is about 70% of GDP. When consumers perceive volatility in the outlook, they tend to reduce their expenditures on goods and services to smooth their consumption over the horizon (e.g., [19], [1], [34]). This prudent behavior affects bank lending as businesses cut back their borrowing in response to the drop in consumer expenditures.[28]

Smaller impact arising from business sentiment volatility may be explained by the fact that banks have a close relationship with the firms that they lend to, and that banks monitor the performance of business to make sure that their loans are repaid as contracted in the first place. Hence, high outlook volatility perceived by business leaders may not necessary affect banks' views about the firms' ability to payback their loans. In fact, according to option theory, rising business sentiment uncertainty may stimulate banks to wait for new information before calling funds back to avoid losing established linkages with businesses and extend further loans to help businesses achieve higher profits as they go into new ventures (e.g., [24], [36]). In this context, the role of business sentiment volatility differs considerably from that of leading indicator volatility, as leading indicator volatility measures the health of the overall economic environment, whereas business volatility refers to how businesses perceive the future from businesses perspective given the options available to them.

These observations support the findings reported in earlier research which has examined the uncertainty effects on bank lending behavior. Research has widely acknowledged that banks tend to curtail their loan supply after monetary and financial shocks, making it difficult for bank-dependent borrowers to rely on external finance.[29] We show that as banks' risk preferences changes while uncertainty varies over time, bank managers would be more willing to extend loans during periods of tranquility and less so when uncertainty reaches extreme levels, because, in general, lenders suffer less from asymmetric information problems during the expansionary state of the economy. In addition, because monitoring costs also change with the the changes in

[28] See [12] who argues that volatility bursts cause a rapid drop and rebound in aggregate output and employment, as firms temporarily paused their investment and hiring activities.

[29] See for instance, [10], [31], [26].

economic environment, this may further affect the availability of bank credit.

5.3 Do Bank-specific variables affect transmission of uncertainty effects?

In this section, we scrutinize the evolution of bank credit by examining whether the adverse effects of sentiment volatility is transmitted on bank loan growth through bank-specific variables. Table 5 reports our main results. Once again, all models contain macroeconomic control variables, year and firm-specific effects. The first three rows provide the effect of sentiment ($\Delta Sent$), sentiment volatility ($\hat{\sigma}_{Sent}$), and the extreme cases ($\hat{\sigma}_{Sent} \times \hat{\sigma}^{asm}$) to provide a basis for the analysis. The effects of change in sentiment, its volatility and extreme sentiment are similar to that reported in Table 4. The only difference emerges with the effect of business confidence volatility, which is insignificant, possibly due to the additional interaction terms that we introduced into the model.

We next look at the impact of bank-specific variables on bank loan growth as sentiment volatility changes. The effect of Tier-1 capital has a positive effect on loan growth regardless of the level of volatility. Furthermore, the interaction between Tier-1 and uncertainty does not receive a significant coefficient. Similarly, the effect of bank liquidity is always positive and significant, and this relation does not change with the extent of sentiment volatility. Hence, we conclude that the impact of sentiment volatility on bank loan growth does not transmit through Tier-1 capital or liquidity.

Impaired loans continue to play a negative role on banks' loan growth. The double interaction terms with sentiment volatility is negative and significant in four out of six cases. The effect of extreme volatility is positive and significant only for the case of consumer sentiment (see the triple interaction). Turning to the role of size, we find that it has a negative impact on loan growth, echoing our earlier findings. The interaction terms associated with size assume positive or negative signs. Under extreme volatility, the effect is negative except for consumer sentiment volatility.

Lastly, we turn to the effect of return on assets on bank loan growth. We find that the own effect of asset returns has a significant negative effect, as we observed in our earlier tables. However, when we look at the sign associated with the double interactions, we find that these coefficients are consistently significant and positive, yet, the triple interaction coefficients are negative and significant. These coefficient estimates indicate that although banks with lower return on assets are more aggressive in periods of tranquility, when the environment is volatile, banks with lower returns on assets reduce their credit growth more sharply than those banks with higher returns.

Our results provide evidence that the source of the level and volatility of sentiment have different effects on banks' loan growth through. Especially, our findings show that sentiment volatility effects differ due to differing transmission on bank loans through various bank-specific variables. Given our findings, future studies should consider the transmission of volatility effects through bank variables, as their omission could lead to biased conclusions regarding banks' lending behavior.

5.4 Robustness check and additional evidence

Results that we have provided to this stage show that the source of the level and volatility of sentiment have differing effects on banks' loan growth through. Furthermore, the impact of sentiment volatility may affect banks' lending behavior depending on the other bank-specific variables. To examine the robustness of our observations we next carry out the investigation for net loan growth and depict the results in Table 6. The table presents our findings for the widest model which allows for double and triple interactions. The first two columns present the results for the changes and volatility that arise from the leading indicator, columns 3-4 and the last two columns present results for the business and consumer sentiment, respectively. These results are very similar to our earlier findings providing support to our claim that the level and sentiment volatility affects bank loans and that this effect varies with respect to its source.

To further check the robustness of our results, we re-estimated our models using commercial banks only and obtained similar observations. Lastly, the inclusion of stock price volatility into the model did not alter our main conclusions. To save space, we do not report these results but they are available upon request.

6 Conclusion

Different from the literature, this study investigates the effects of changes and volatility of economic agents' sentiment on banks' lending behavior. We particularly focus on three different composite sentiment indicators which provide a broad perspective of the economic agents' beliefs about the state of the economy: these are business sentiment, consumer sentiment and leading indicators. To carry out the analysis, we construct a bank-level panel data set that is comprised of thousands of banks extracted from the Bankscope database for the G7 countries including Canada, France, Germany, Italy, Japan, the UK, and the US. The data cover the period between 1999-2014. Using GMM and fixed effects models, we show that changes and volatility of sentiment have a negative and significant impact on banks' loan growth. We also find that banks further reduce their loan growth when sentiment volatility reaches excessive levels.

Throughout our our analysis, we examine the impact of several bank-specific variables, including capital strength, impaired loans, size, liquidity and return on assets. We find that sentiment volatility transmits its effects on bank loan growth through these variables. In particular, we observe that i) banks further reduce their loans if banks carry higher impaired loans under higher volatility; ii) banks with higher return on assets are less affected by uncertainty; iii) as bank size increases, uncertainty effect on bank loans dampens. Interestingly, even though both high quality bank capital (i.e., Tier-1 bank capital) and liquidity play a vital role in credit growth, these variables do not play a role in the transmission of sentiment uncertainty on bank lending behavior.

Overall, given our observations in this study and findings from the literature, we argue that sentiment measures should not be omitted in examining bank behavior. Omission of these elements from the model may lead to biased conclusions. In addition, it would be interesting to examine the role of other types of sentiment measures such as market-based measures and text-based measures on banks' lending behavior. We shall leave these issues for future work.

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Table 1: Variable definitions

Variable	Definition	Source
A. Dependent variables		
Δln_GL	Logarithmic first difference of total loans.	Bankscope
Δln_NL	Logarithmic first difference of net loans.	Bankscope
B. Bank-level variables		
Tier 1 ratio (Tier1)	This ratio is measured by the shareholder funds plus perpetual non-cumulative preference shares as a percentage of risk weighted assets and off-balance sheet risks measured under the Basel rules.	Bankscope
Impaired loans to Gross Loans (Impaired_GL)	This ratio measures the amount of total loans which are impaired or doubtful. Therefore, the lower this figure is the better the asset quality is.	Bankscope
Size		

	Natural logarithm of the bank's total assets (millions of dollars).	Bankscope
Liquid Asset to Total deposits and short-term borrowing (Liquid_Tdb)	This ratio looks at what percentage of total customer deposits and other short-term funds could be met if they were withdrawn suddenly, the higher this percentage the more liquid the bank is and less vulnerable to a classic run on the banks.	Bankscope
Return on Average Assets (ROAA)	This ratio measures the returns generated from the assets financed by the bank to compare banks' relative efficiency and their operational performance.	Bankscope
C: Macroeconomic variables		
$GDPGr$	Logarithmic first difference of GDP (percent)	Datastream
IR	Long-term	Datastream

	interest rates (percent)	
D: Sentiment variables		
Composite Leading Indicator (CLI)	CLI is an aggregate time series displaying a reasonably consistent leading relationship with the reference series (e.g., industrial production up to March 2012 and GDP afterwards) for the macroeconomic cycle in a country. Note that the component series for each country are selected based on various criteria such as economic significance, cyclical behavior, data quality, timeliness and availability. CLI is designed to provide early signals of turning points (peaks and troughs) between expansions and slowdowns of	

	economic activity.
Business Sentiment Indicator (BCI)	BCI is a composite sentiment indicator that summarizes managers' assessments and expectations of the general economic situation.
Consumer Sentiment Indicator (CCI)	CCI include indicators on consumer confidence, expected economic situation and price expectations.

Table 2: Descriptive statistics

	Canada		**Germany**		**France**		**UK**		**Italy**		**Japan**		**US**		**G7**	
Panel A: Basic Information																
No. of Banks	41		1394		36		49		529		161		7109		9319	
No. of Obs	193		3712		236		265		4301		1772		97978		108457	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
$NLTA$	0.618	0.223	0.568	0.142	0.439	0.218	0.473	0.194	0.657	0.153	0.621	0.133	0.626	0.155	0.624	0.156
$GLTA$	0.626	0.225	0.568	0.575	0.452	0.228	0.488	0.204	0.677	0.155	0.634	0.136	0.635	0.157	0.634	0.157
Panel B: Bank-specific Variables																

Δln_N	11.133	39.344	5.938	8.798	6.535	19.480	3.663	26.171	8.236	15.018	2.466	13.107	7.961	22.703	7.830	22.165
Δln_G	11.142	39.151	5.942	8.890	6.538	19.717	4.076	25.562	8.915	15.096	2.366	12.928	7.993	22.617	7.884	22.085
$Tier1$	19.553	10.850	12.616	4.648	13.687	9.459	13.502	6.228	16.528	10.387	8.734	6.014	17.535	14.156	17.169	13.755
$Impai$	1.248	2.036	4.090	3.755	4.121	2.645	5.493	6.483	8.833	5.628	5.185	3.004	1.609	2.960	1.996	3.447
$Size$	8.377	2.636	6.729	1.693	11.155	2.683	10.050	2.461	6.523	1.647	10.047	1.224	4.959	1.325	5.197	1.612
$Liquid$	25.763	24.935	14.409	11.425	35.561	23.915	34.489	19.308	15.006	15.303	8.736	7.826	11.555	16.041	11.863	15.945
$ROAA$	1.302	3.127	0.280	0.433	0.485	0.579	0.120	1.996	0.471	1.000	0.022	2.027	0.780	1.394	0.737	1.385
Panel C: Macroeconomic Variables																
ΔGDP	2.347	1.379	0.934	2.123	1.082	1.664	1.035	2.112	-0.512	2.396	0.858	2.257	2.059	1.790	1.894	1.920
$IR(\%)$	3.429	1.085	2.079	0.736	3.749	0.768	4.030	0.638	4.027	0.941	1.820	0.366	4.629	1.006	4.466	1.148
Panel D: Sentiment Variables																
ΔCLI	0.033	1.089	0.009	1.945	-0.018	1.174	0.068	1.308	0.034	1.358	0.160	1.190	0.010	1.560	0.042	1.364
ΔBCI	-	-	0.024	1.613	-0.073	0.929	0.151	1.277	-0.033	0.970	0.186	1.125	0.072	1.122	0.055	1.166
ΔCCI	-0.008	0.835	0.057	1.503	-0.060	0.696	0.060	1.050	-0.067	0.950	0.056	1.426	-0.152	0.992	-0.016	1.072
σ_{CLI}	0.007	0.002	0.009	0.005	0.006	0.001	0.008	0.003	0.007	0.002	0.006	0.001	0.009	0.005	0.008	0.003
σ_{BCI}	-	-	0.010	0.003	0.008	0.001	0.018	0.002	0.008	0.001	0.005	0.002	0.021	0.005	0.012	0.006
σ_{CCI}	0.02	0.00	0.01	0.00	0.01	0.00	0.02	0.00	0.01	0.00	0.01	0.00	0.02	0.00	0.01	0.00

	4	7	6	1	1	1	0	4	8	6	3	6	3	7	8	7

Table 3: Correlation between variables

	Δln_NI	$Tier1$	Imp	$Size$	Liq_Td	$ROAA$		ΔBCI			$\hat{\sigma}^2_{BCI}$	$\hat{\sigma}^2_{CC}$
$\Delta ln\_$	1											
$Tier$	0.358 ^*** ***	1										
Imp	-0.193 ^*** ***	-0.0831 ^*** ***	1									
$Size$	-0.103 ^*** ***	-0.233 ^*** ***	0.302 ^*** ***	1								
$Liq\_$	0.257 ^*** ***	0.537 ^*** ***	0.126 ^*** ***	-0.0249 ^*** ***	1							
ROA	-0.128 ^*** ***	-0.135 ^*** ***	-0.299 ^*** ***	-0.0415 ^*** ***	-0.184 ^*** ***	1						
ΔCL	-0.00276	0.0201 ^*** ***	0.00190	0.00695 ^* *	0.00576 ^* *	0.0512 ^*** ***	1					
ΔBC	-0.0438 ^*** ***	-0.00159	0.0425 ^*** ***	-0.00190	0.00140	0.00389	0.776 ^*** ***	1				
ΔCC	-0.0340	0.00647 ^* *	0.0860 ^*** ***	0.0589 ^***	0.0407 ^***	0.0110	0.641 ^***	0.678 ^***	1			

	^*** ***			***	***	^*** ***	***	***				
$\hat{\sigma}_{CLI}$	-0.101 ^*** ***	-0.0252 ^*** ***	-0.0129 ^*** ***	-0.0577 ^*** ***	-0.0360 ^*** ***	-0.0859 ^*** ***	-0.542 ^*** ***	-0.152 ^*** ***	-0.225 ^*** ***	1		
$\hat{\sigma}_{BCI}$	-0.0157 ^*** ***	0.0166 ^*** ***	-0.281 ^*** ***	-0.386 ^*** ***	-0.128 ^*** ***	0.0742 ^*** ***	-0.269 ^*** ***	-0.0289 ^*** ***	-0.238 ^*** ***	0.557 ^*** ***	1	
$\hat{\sigma}_{CCI}$	0.00443	0.0273 ^*** ***	-0.165 ^*** ***	-0.214 ^*** ***	-0.0801 ^*** ***	0.0668 ^*** ***	-0.175 ^*** ***	-0.292 ^*** ***	-0.156 ^*** ***	0.217 ^*** ***	0.455 ^*** ***	1
^* * $p < 0.05$, ^** ** $p < 0.01$, ^*** *** $p < 0.001$												

Table 4: Results from the basic bank lending model

	(Δln_NL)		(Δln_GL)	
	FE	GMM	FE	GMM
Δln_NL		0.0813 ^*** ***		
		(0.015)		
$\Delta ln\_GL_($				0.0848 ^*** ***
				(0.014)
$Tier1_{t-}$	0.00603 ^*** ***	0.00527 ^*** ***	0.00601 ^*** ***	0.00455 ^*** ***
	(0.001)	(0.002)	(0.001)	(0.002)
$Impaired\_GL_t$	-0.0169 ^*** ***	-0.00752 ^* *	-0.0171 ^*** ***	-0.00777 ^* *
	(0.001)	(0.004)	(0.001)	(0.004)
$Size_{t-1}$	-0.188 ^*** ***	-0.289 ^*** ***	-0.186 ^*** ***	-0.283 ^*** ***

	(0.008)	(0.041)	(0.008)	(0.041)
Liq_Tdl	0.00236 ^*** ***	0.00237 ^** **	0.00237 ^*** ***	0.00269 ^** **
	(0.000)	(0.001)	(0.000)	(0.001)
$ROAA_{t-}$	-0.0115 ^*** ***	0.00854	-0.0114 ^*** ***	0.00806
	(0.002)	(0.007)	(0.002)	(0.007)
ΔGDP	0.00125	-0.0156 ^* *	-0.000392	-0.0120
	(0.001)	(0.009)	(0.001)	(0.009)
IR	-0.00179	-0.0420	0.00107	-0.0403
	(0.002)	(0.028)	(0.002)	(0.027)
$Cons$	0.912 ^*** ***		0.894 ^*** ***	
	(0.047)		(0.046)	
N	97196	80806	97196	80806
R^2	0.422		0.423	
AR2 test (p_value)		0.590		0.587
Hansen J test (p_value)		0.138		0.082
Standard errors in parentheses				
^* * $p < 0.10$, ^** ** $p < 0.05$, ^*** *** $p < 0.01$				

Table 5: The effects of sentiment on credit growth

	Leading Indicator		Business Sentiment		Consumer Sentiment	
	(1)	(2)	(3)	(4)	(5)	(6)
$L.Tier1$	0.00601 ^*** ***	0.00602 ^*** ***	0.00602 ^*** ***	0.00602 ^*** ***	0.00606 ^*** ***	0.00606 ^*** ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$L.Impaired\_G$	-0.0167 ^*** ***	-0.0167 ^*** ***	-0.0168 ^*** ***	-0.0169 ^*** ***	-0.0170 ^*** ***	-0.0171 ^*** ***

	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$L.Size$	-0.188 ^*** ***	-0.187 ^*** ***	-0.189 ^*** ***	-0.189 ^*** ***	-0.187 ^*** ***	-0.187 ^*** ***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$L.Liq\_T$	0.00238 ^*** ***	0.00237 ^*** ***	0.00236 ^*** ***	0.00235 ^*** ***	0.00234 ^*** ***	0.00234 ^*** ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$L.ROAA$	-0.0115 ^*** ***	-0.0115 ^*** ***	-0.0115 ^*** ***	-0.0116 ^*** ***	-0.0115 ^*** ***	-0.0116 ^*** ***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$L.\Delta CLI$	-0.0203 ^*** ***	-0.0146 ^*** ***				
	(0.002)	(0.002)				
$L.\hat{\sigma}_{CLI}$	-7.163 ^*** ***	-6.425 ^*** ***				
	(0.616)	(0.594)				
$L.\hat{\sigma}_{CLI} \times \hat{\sigma}^{asm}$		-5.899 ^*** ***				
		(0.549)				
$L.\Delta BCI$			-0.00904 ^*** ***	-0.00603 ^** **		
			(0.003)	(0.003)		
$L.\hat{\sigma}_{BCI}$			-0.693 ^* *	-0.760 ^* *		
			(0.401)	(0.402)		
$L.\hat{\sigma}_{BCI} \times \hat{\sigma}^{asm}$				-3.046 ^*** ***		
				(0.267)		
$L.\Delta CCI$					0.00304	-0.00596 ^*** ***

					(0.002)	(0.002)
$L.\hat{\sigma}_{CCI}$					-4.161 ^*** ***	-4.646 ^*** ***
					(0.263)	(0.257)
$L.\hat{\sigma}_{CCI} \times \hat{\sigma}^{asm}$						2.124 ^*** ***
						(0.169)
N	97196	97196	97097	97097	97196	97196
R^2	0.422	0.423	0.423	0.423	0.423	0.424
Standard errors in parentheses						
^* * $p < 0.10$, ^** ** $p < 0.05$, ^*** *** $p < 0.01$						

Table 6: The effects of sentiment on credit growth including interactions with sentiment volatility

	Leading Indicators		Business Sentiments		Consumer Sentiments	
	(1)	(2)	(3)	(4)	(5)	(6)
$L.\Delta Sen$	-0.0200 ^*** ***	-0.0169 ^*** ***	-0.0112 ^*** ***	-0.00709 ^** **	0.00291	-0.00628 ^*** ***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
$L.\hat{\sigma}_{Sent}$	-4.976 ^** **	-5.436 ^*** ***	0.106	-0.398	-4.673 ^*** ***	-5.578 ^*** ***
	(2.115)	(1.840)	(1.789)	(1.512)	(0.903)	(0.910)
$L.\hat{\sigma}_{Sent}$ $\hat{\sigma}^{asm}$		-5.725 ^*** ***		-2.115 ^*** ***		1.982 ^*** ***
		(0.585)		(0.580)		(0.226)
$L.Tier1$	0.00671 ^*** ***	0.00559 ^*** ***	0.00716 ^*** ***	0.00747 ^*** ***	0.00693 ^*** ***	0.00894 ^*** ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$L.Tier1 \times \hat{\sigma}_{Sent}$	-0.0844	0.0805	-0.0653	-0.0883	-0.0385	-0.149
	(0.097)	(0.079)	(0.073)	(0.060)	(0.026)	(0.121)

$L.Tier1 \times \hat{\sigma}_{Sent} \times \hat{\sigma}^{asm}$		-0.114		0.00465		0.0589
		(0.076)			(0.047)	(0.062)
$L.Impaired\_G$	-0.0174 ^*** ***	-0.0162 ^*** ***	-0.0126 ^*** ***	-0.0130 ^*** ***	-0.0148 ^*** ***	-0.0101 ^*** ***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
$L.Impaired\_G \times \hat{\sigma}_{sent}$	0.0842	-0.0181	-0.173 ^*** ***	-0.154 ^* *	-0.0930 ^* *	-0.362 ^*** ***
	(0.061)	(0.246)	(0.065)	(0.087)	(0.056)	(0.100)
$L.Impaired\_G \times \hat{\sigma}_{Sent} \times \hat{\sigma}^{asm}$		0.0707		0.00955		0.124 ^*** ***
		(0.161)		(0.039)		(0.044)
$L.Size$	-0.181 ^*** ***	-0.186 ^*** ***	-0.188 ^*** ***	-0.201 ^*** ***	-0.192 ^*** ***	-0.188 ^*** ***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
$L.Size \times \hat{\sigma}_{Sent}$	-0.378 ^** **	0.398 ^* *	0.114	0.760 ^*** ***	0.156 ^* *	0.0600
	(0.155)	(0.238)	(0.153)	(0.199)	(0.086)	(0.123)
$L.Size \times \hat{\sigma}_{Sent} \times \hat{\sigma}^{asm}$		-0.510 ^*** ***		-0.325 ^*** ***		0.0934 ^* *
		(0.123)		(0.067)		(0.049)
$L.Liq\_T$	0.00200 ^*** ***	0.00331 ^*** ***	0.00209 ^** **	0.00317 ^** **	0.00176 ^** **	0.00166 ^* *
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$L.Liq\_Tdb \times \hat{\sigma}_{Sent}$	0.0393	-0.174	0.0105	-0.0572	0.0251	0.0297
	(0.033)	(0.131)	(0.040)	(0.074)	(0.031)	(0.049)
$L.Liq\_Tdb \times \hat{\sigma}_{Sent} \times \hat{\sigma}^{asm}$		0.141		0.0397		-0.00346
		(0.089)		(0.030)		(0.022)

$L.ROAA$	-0.0264 ^*** ***	-0.0435 ^*** ***	-0.0448 ^*** ***	-0.0596 ^*** ***	-0.0153 ^*** ***	-0.0318 ^*** ***
	(0.003)	(0.005)	(0.006)	(0.007)	(0.004)	(0.007)
$L.ROAA \times \hat{\sigma}_{Sent}$	1.292 ^*** ***	3.990 ^*** ***	1.495 ^*** ***	2.444 ^*** ***	0.169	1.005 ^*** ***
	(0.218)	(0.638)	(0.218)	(0.354)	(0.171)	(0.308)
$L.ROAA \times \hat{\sigma}_{Sent} \times \hat{\sigma}^{asm}$		-1.877 ^*** ***		-0.465 ^*** ***		-0.490 ^*** ***
		(0.404)		(0.124)		(0.130)
N	97196	97196	97097	97097	97196	97196
R^2	0.425	0.427	0.426	0.428	0.423	0.426

Standard errors in parentheses; ^* * $p < 0.10$, ^** ** $p < 0.05$, ^*** *** $p < 0.01$

Table 7: Robustness check using gross loan growth

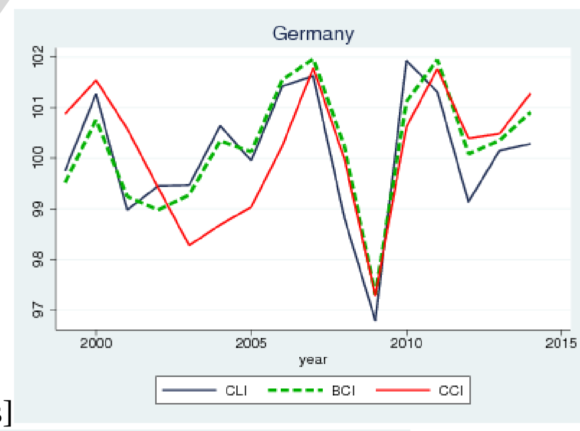
	Leading Indicators		Business Sentiments		Consumer Sentiments	
	(1)	(2)	(3)	(4)	(5)	(6)
$L.\Delta Sen$	-0.0214 ^*** ***	-0.0183 ^*** ***	-0.00977 ^*** ***	-0.00575 ^** **	0.00203	-0.00729 ^*** ***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
$L.\hat{\sigma}_{Sent}$	-4.647 ^** **	-5.058 ^*** ***	0.178	-0.261	-4.511 ^*** ***	-5.418 ^*** ***
	(2.102)	(1.832)	(1.779)	(1.504)	(0.898)	(0.905)
$L.\hat{\sigma}_{Sent} \times \hat{\sigma}^{asm}$		-5.610 ^*** ***		-2.219 ^*** ***		2.023 ^*** ***
		(0.574)		(0.574)		(0.223)
$L.Tier1$	0.00671 ^*** ***	0.00559 ^*** ***	0.00714 ^*** ***	0.00744 ^*** ***	0.00694 ^*** ***	0.00893 ^*** ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$L.Tier1$ $\hat{\sigma}_{Sent}$	-0.0878	0.0790	-0.0653	-0.0877	-0.0397	-0.150

	(0.096)	(0.080)	(0.072)	(0.060)	(0.026)	(0.120)
$L.Tier1 \times \hat{\sigma}_{Sent} \times \hat{\sigma}^{asm}$		-0.116		0.00439		0.0585
		(0.076)		(0.046)		(0.062)
$L.Impaired\_G$	-0.0177 ^*** ***	-0.0167 ^*** ***	-0.0132 ^*** ***	-0.0135 ^*** ***	-0.0148 ^*** ***	-0.0107 ^*** ***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
$L.Impaired\_G \times \hat{\sigma}_{sent}$	0.0974	0.00882	-0.156 ^*** ***	-0.138 ^* *	-0.101 ^* *	-0.333 ^*** ***
	(0.062)	(0.215)	(0.059)	(0.078)	(0.052)	(0.089)
$L.Impaired\_G \times \hat{\sigma}_{Sent} \times \hat{\sigma}^{asm}$		0.0616		0.0119		0.105 ^*** ***
		(0.139)		(0.039)		(0.040)
$L.Size$	-0.179 ^*** ***	-0.184 ^*** ***	-0.186 ^*** ***	-0.198 ^*** ***	-0.190 ^*** ***	-0.187 ^*** ***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)
$L.Size \times \hat{\sigma}_{Sent}$	-0.373 ^** **	0.360	0.0884	0.688 ^*** ***	0.138	0.0659
	(0.154)	(0.234)	(0.152)	(0.197)	(0.086)	(0.122)
$L.Size \times \hat{\sigma}_{Sent} \times \hat{\sigma}^{asm}$		-0.481 ^*** ***		-0.303 ^*** ***		0.0799 ^* *
		(0.121)		(0.066)		(0.048)
$L.Liq\_T$	0.00201 ^*** ***	0.00335 ^*** ***	0.00213 ^** **	0.00320 ^** **	0.00176 ^** **	0.00170 ^* *
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$L.Liq\_Tdb \times \hat{\sigma}_{Sent}$	0.0387	-0.178	0.00893	-0.0581	0.0258	0.0276
	(0.033)	(0.130)	(0.040)	(0.073)	(0.030)	(0.049)
$L.Liq\_Tdb \times \hat{\sigma}_{Sent} \times \hat{\sigma}^{asm}$		0.144		0.0393		-0.00202

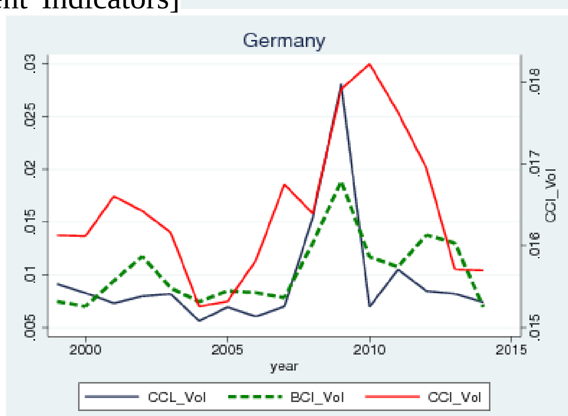
		(0.089)		(0.029)		(0.021)
$L.ROAA$	-0.0262 ∧*** ***	-0.0434 ∧*** ***	-0.0447 ∧*** ***	-0.0601 ∧*** ***	-0.0158 ∧*** ***	-0.0316 ∧*** ***
	(0.003)	(0.005)	(0.006)	(0.007)	(0.004)	(0.007)
$L.ROAA$ $\hat{\sigma}_{Sent}$	1.281 ∧*** ***	4.000 ∧*** ***	1.494 ∧*** ***	2.479 ∧*** ***	0.192	0.995 ∧*** ***
	(0.218)	(0.638)	(0.219)	(0.356)	(0.170)	(0.307)
$L.ROAA \times \hat{\sigma}_{Sent} \times \hat{\sigma}^{asm}$		-1.892 ∧*** ***		-0.483 ∧*** ***		-0.471 ∧*** ***
		(0.402)		(0.125)		(0.128)
N	97196	97196	97097	97097	97196	97196
R^2	0.426	0.428	0.427	0.429	0.424	0.427

Standard errors in parentheses; ∧* * $p < 0.10$, ∧** ** $p < 0.05$, ∧*** *** $p < 0.01$

[Germany Sentiment Indicators]

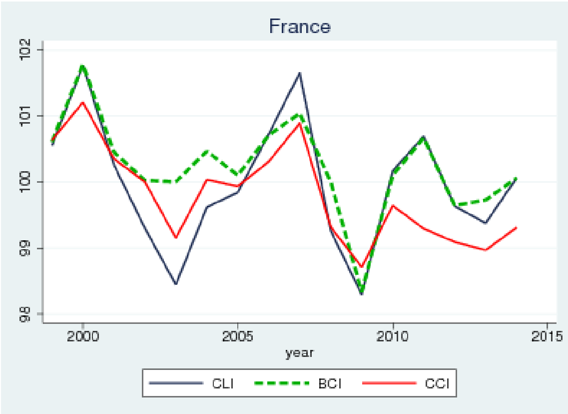


[Germany Sentiment Volatilities]

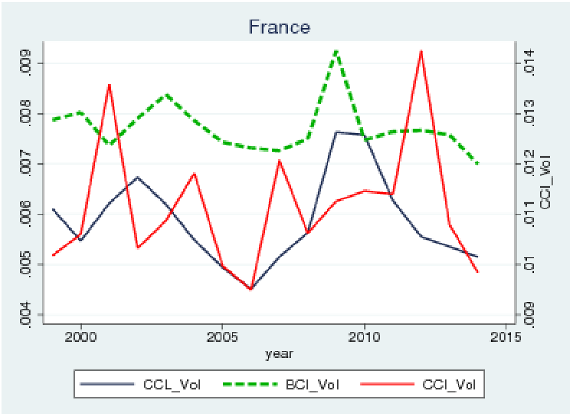


[France Sentiment

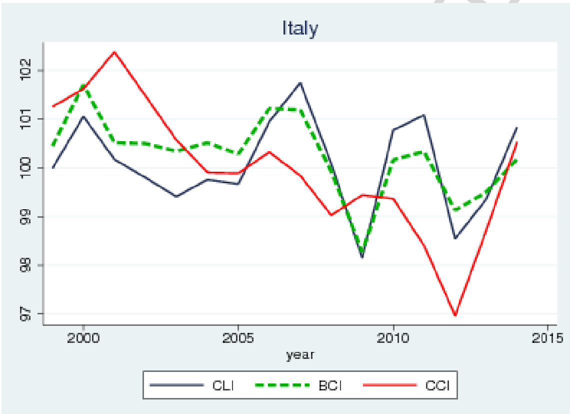
Indicators]



[France Sentiment Volatilities]



[Italy Sentiment Indicators]



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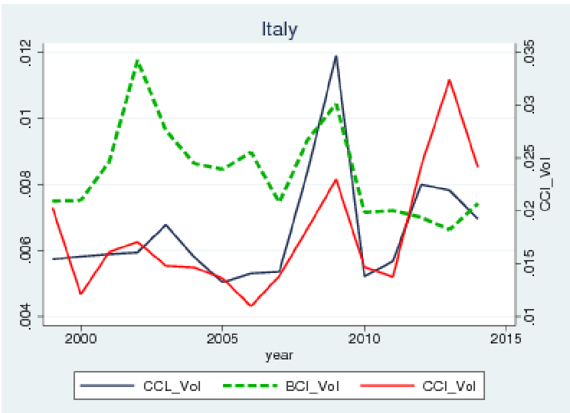
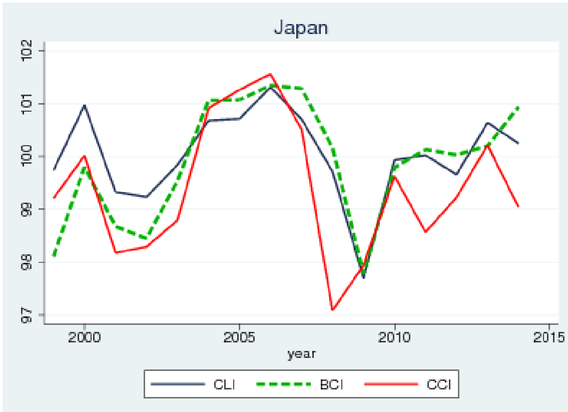
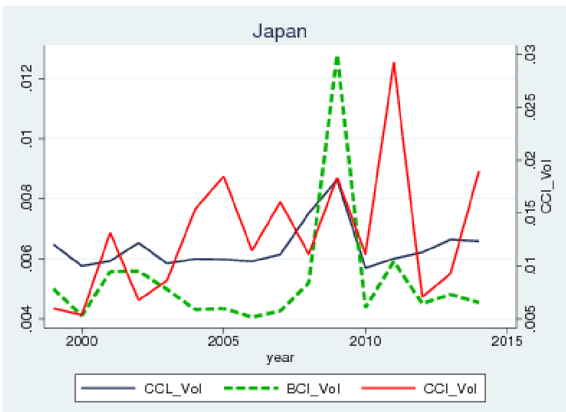


[Japan Sentiment Indicators]

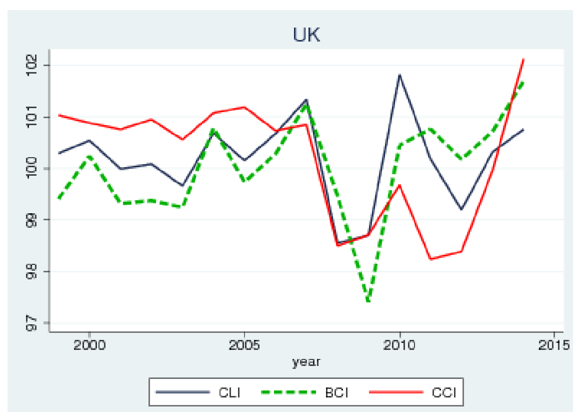




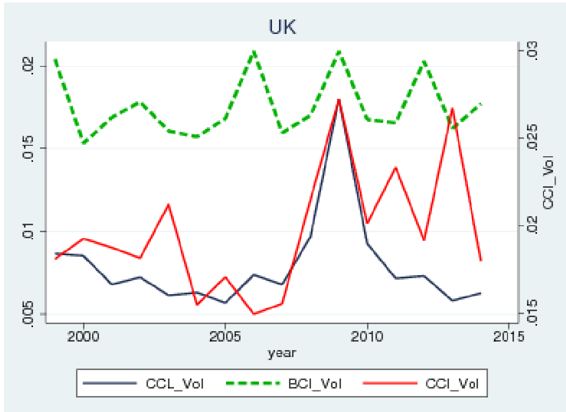
[Japan Sentiment Volatilities]

Figure 1: The level of sentiments and their volatility

[UK Sentiment Indicators]

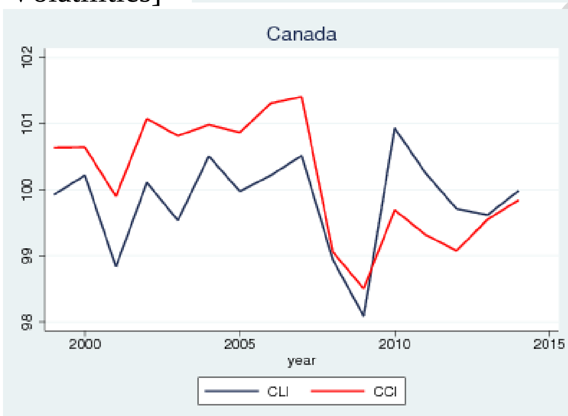


[UK



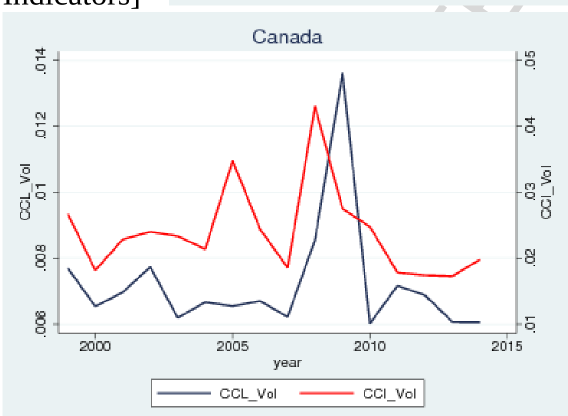
Sentiment Volatilities]

[Canada Sentiment

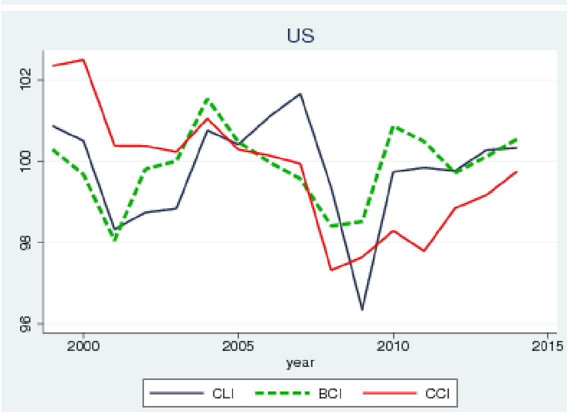


Indicators]

[Canada Sentiment Volatilities]



[US Sentiment Indicators]



[US Sentiment Volatilities]

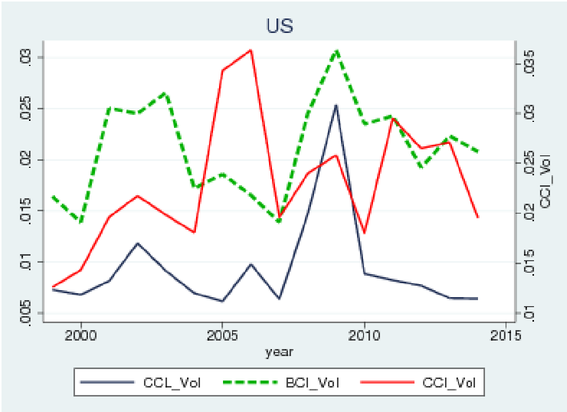


Figure 2: The level of sentiments and their volatility