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277

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PERCEIVED VS ACTUAL FINANCIAL CRISIS AND BANK CREDIT STANDARDS: IS THERE ANY INDICATION OF SELF-FULFILLING PROPHECY?

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Abstract

We link senior banks loan officers' responses regarding their decisions for bank credit standards, from successive surveys from the European Bank Lending Survey to investigate two important issues. First, we examine the relationship between bank credit standards (CS) and perceived and actual financial crisis. Second, we investigate whether the notion of the self-fulfilling prophecy is applicable in the case of the 2008 global financial crisis. In particular, the second main research question that we try to answer is whether the perceived crisis (as implied by the Google search query "financial crisis") contributed to the acceleration of the outburst of the actual crisis. We find that both perceived and actual financial crisis affect senior bank loan officers' credit standards, with the actual crisis having the greatest impact. These results are consistent both in the short and in the long run. Finally, by putting forward a binary choice model we find sufficient evidence to support the Self-Fulfilling Prophecy notion.

Keywords: Credit Standards; Financial Crisis; Google Trends; Crisis Sentiment; Self-Fulfilling Prophecy.

JEL-Classification: C51, E30, E32, E44, E51, G01, G21.

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"What information consumes is rather obvious: it consumes the attention of its recipients. Hence, a wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it."[1]

Herbert Simon, Nobel Laureate in Economics.

1. Introduction

The recent economic crisis has vividly underlined the central role of the stability of the financial intermediaries and its role in enhancing the smoothness of the credit transmission to borrowers. The eruption of the crisis and the subsequent credit crunch spawned a great amount of literature which investigated their effects and their causes (see for e.g. Brunnermeier, 2009; Ivashina and Scharfstein, 2010; Puri *et. al.*, 2011; Millon *et. al.*, 2011; Popov and Udell, 2012; Buera *et. al.*, 2015; Richter and Karidis, 2016; Tomczak, 2017; Kosmidou, 2017; Bell, 2018; Huber, 2018). One of the main consequences of the crisis was the abrupt decrease of the general credit availability and the sudden tightening of both banks' loan terms and conditions and credit standards. Hence, the outburst of the 2008 financial crisis generated the so-called credit crunch where pursuant to Bernanke and Lown (1991) "…*a bank credit crunch is a significant leftward shift in the supply curve for bank loans, holding constant both the safe real interest rate and the quality of potential borrowers*".

Despite the indisputable attempts to address the adverse financial consequences of the crisis both by the competent political authorities and economic institutions, the social consequences of the crisis have received less attention. An important factor that has been ignored so far is the public perception of the 2008 global financial crisis. Which was the public crisis sentiment before the outburst of the recent financial crisis? Did this public crisis sentiment affect senior bank loan officers' decisions for forming their lending policies? Did these public expectations for the crisis contribute to the acceleration of the outburst of the actual crisis?

The first step towards the analysis of the public sentiment of the 2008 financial crisis and its impact on bank credit standards (CS hereafter) is its quantification. Google, the greatest online search engine in the world, released in 2004 *Google Trends*, a database from which anyone can obtain data for Google searches across the world.

[1] Designing Organizations for an Information-Rich World, in Martin Greenberger, Computers, Communication, and the Public Interest [Baltimore, MD: The Johns Hopkins Press, 1971, 40–41].

Each search item is called Google Search Volume Index (GSVI hereafter) and is referred to the number of searches for each word/item[2].

In Figure 1 below, we observe a pictorial presentation of the Google search volumes from the Google Trends site.

[Insert Figure 1 here]

Google Trends database offers an opportunity to instrument the public perception of the 2008 financial crisis. In particular, we employ the GSVI "financial crisis" to capture the so-called perceived crisis, that is how people are aware of the search term "financial crisis".

"[…] *as a sequential chain of several rational-imitation mechanisms"* (Merton, 1948; Hedström, 2008) a self-fulfilling prophecy may arise when a preliminary belief - either true or false - results in such a behaviour that sooner or later makes the original belief become reality. Perceived crisis may function as a self-fulfilling prophecy: it is conceivable that individuals who are triggered to search for the word "financial crisis" on Google will make behavioural choices that lead to an aggravation of the economic environment. Hence, it is possible that this perceived crisis contributed to the outbreak of the 2008 financial crisis, indicating the existence of a self-fulfilling prophecy.

The novelty of this study is twofold. First, we employ survey data to examine the relationship between bank loan officers' decisions for bank CS and the perceived vs the actual financial crisis. As perceived financial crisis we propose an index constructed by employing data for the term "financial crisis" from Google Trends and as actual financial crisis we use a dummy variable attaining 0 (before the 2008 financial crisis) and 1 (during/after the financial crisis). Our prior beliefs are that both real and perceived crises will have a significant impact on CS, with the real crisis being the one with the greatest impact. Second, we investigate whether the idea of the self-fulfilling prophecy is applicable in the case of the 2008 global financial crisis. In other words, we study whether the expectations for the crisis (i.e. the perceived crisis) contributed to the acceleration of the outburst of the actual crisis. To the best of our knowledge, this is the first study conducting such an investigation aiming to close a gap in the literature.

[2] According to the official site of Google Trends, GSVI is defined as the ratio between the number of search queries for each keyword to the total Google search queries.

Our findings imply that both the perceived and the actual financial crisis played an important role in shaping seniors' bank loan officers decision regarding CS, consequently affecting the evolution of the credit conditions in the Euro area. Our results also signal that both types of crisis contributed substantially to the existence of more credit constrained firms (i.e. credit crunch) through the path of credit tightness, with the actual economic crisis having the greatest impact. Finally, we find some evidence to support the hypothesis of the self-fulfilling prophecy during the 2008 global financial crisis.

The remainder of the paper is structured as follows: In section 2 we provide a review of the literature, while in section 3 we describe the data. In Section 4 we present the employed baseline econometric models and the econometric methodologies. Section 5 includes the empirical results. Finally, section 6 concludes.

2. Previous empirical findings

Banks are the key providers of funds in the vast majority of economies worldwide. As a consequence, it is very important to realize the mechanisms governing their decisions to grant credit to both households and enterprises. CS provide a core piece of information on these mechanisms in the Euro area. Hence, it is conceivable that CS constitute an essential factor of the banking activity and a key element of the whole economic activity, especially through the path of firms' function (given that the latter is directly reliant on bank lending). That is why in the recent years a rapidly increasing bibliography examines both the momentousness of CS and the factors that affect them. More specifically, many studies investigate the potential drivers of bank CS such as: economic and regulatory bank capital (Enria *et. al.,* 2004), bank competition (Rucks, 2014) and business cycle (Anastasiou *et. al.,* 2018). Other authors focus on the interconnection of CS with monetary policy (Cappiello *et. al.,* 2010; Maddaloni and Peydró, 2011). Another interesting branch of the literature examines the leading indicator properties of other BLSs for the US (Lown *et. al.,* 2000; Lown and Morgan 2002 and Lown and Morgan, 2006). In the same vein, there exist a number of research papers which incorporate survey-based information on bank CS in order to develop different types of financial conditions indices (Swiston, 2008; Guichard *et. al.,* 2009;

Hatzius *et. al.*, 2010; Altavilla, Darracq-Paries, and Nicoletti, 2015). However, whether both perceived and actual economic crisis influence CS has not been examined thus far.

The invasion of Google trends in the economic literature can be considered as very recent since it has taken place in the last decade. The relevant bibliography covers a various set of economic issues. To be more precise, many researchers employ google queries as an indicator of public sentiment to examine several aspects of economic activity such as: employment/unemployment (Askitas and Zimmermann, 2009; Choi and Varian, 2009; Fondeur and Karamé, 2013), economic prediction (Choi and Varian, 2012), private consumption (Penna and Huang, 2009, Vosen and Schmidt 2011, 2012), growth cycle analysis (Suhoy, 2009), volatility market phases (Hamid and Heiden, 2015), stock-trading (Takeda and Wakao, 2014), house sales (Wu and Brynjolfsson, 2015) and tourism (Siliverstovs and Wochner, 2018). A remarkable contribution in the literature was the usage of Google trends for the creation of indexes that quantify the sentiment of people regarding several issues of economic activity. Some examples of this stance of the literature are the following: the consumer sentiment index of Penna and Huang (2009), the usage of the Google search volume index (GSVI) to examine trade and investment activities by Li *et. al.*, (2015) and finally, the index of D'Amuri and Marcucci (2017) for the prediction of the unemployment rate.

Having all these as a springboard, we set out to investigate: (i) whether country-level CS (averaged across banks) are affected by the perceived and the actual 2008 financial crisis and (ii) whether the perceived crisis of Google searches redounded to the outbreak of the 2008 financial crisis.

3. Data and variables

Every quarter, the European Central Bank (ECB) requests senior bank lending officers in the euro area to answer a questionnaire with questions about the lending conditions in the euro area. After the collection of the raw responses, the ECB constructs an index, named the diffusion index which as it increases (decreases) denotes tighter (easier) CS. Data for the diffusion index are then provided by the Bank Lending Survey (BLS). Pursuant to the BLS Glossary[3], CS are generally defined as the loan approval criteria that each bank sets. We obtain quarterly data for CS from the BLS for

[3] https://www.ecb.europa.eu/stats/pdf/ecbblsglossary.en.pdf

the period 2004Q1-2016Q1 for 14 euro area countries[4]. Thus, our panel dimensions are time (quarters) and cross-section (countries).

Below we present the relevant question from the questionnaire of BLS:

> ***Question Q1****: Over the past three months, how have your bank's credit standards as applied to the approval of loans or credit lines to enterprises changed?*
>
> ***Answer:***
> - *Tightened considerably*
> - *Tightened somewhat*
> - *Remained basically unchanged*
> - *Eased somewhat*
> - *Eased considerably*

Source: Bank Lending Survey Questionnaire, Section 1: Loans or credit lines to enterprises, question Q1, page 2/19.

This so-called diffusion index describes senior bank loan officers' decisions for tightening or not the CS of their banks. An excess tightening of bank CS could lead firms to be credit constrained. According to the ECB's definition of the diffusion index, the greater (lower) the index is, the more tightened (eased) the CS are. Consequently, a country with a relatively high (low) diffusion index indicates that the CS are stricter (softer). As we can see from Table 1, pursuant to our data, Cyprus, Greece, Italy, and Lithuania are some representative examples of countries with tightened CS, whereas Belgium, Germany, Slovenia, and Portugal are countries with the most eased CS in our sample.

[Insert Table 1 here]

We now turn our attention to the explanatory variables that we employ, a short description of which can be found at Table 2. More precisely, Table 2 provides the definition of each variable, its expected sign and the source from which we obtained it.

[Insert Table 2 here]

The two main variables that we examine as determinants of CS and which describe the perceived and the actual financial crisis are defined as follows:

[4] The Euro area countries that we could include in our sample are with alphabetical order the following: Austria, Belgium, Cyprus, Estonia, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Portugal, Slovenia and Spain. Data for the rest five Eurozone countries were not provided/available.

FC^P: As perceived financial crisis we employ data for the search term "financial crisis" obtained from Google Trends[5]. As this GSVI increases it signifies that more people searched for this term for the period under examination. The more Google searches there are the greater the implied fear is and hence a positive sign is expected. This index signifies how people understand/perceive the financial crisis. Hence, it is a good proxy to measure the so-called *perceived crisis*. As the number of Google searches for "financial crisis" increases so more people are aware of this term.

FC^A: As actual financial crisis we use a dummy variable which takes values 0 (if we are before the 2008 financial crisis) and 1 (if we are during/after the financial crisis). In particular, the actual financial crisis is defined as follows:

$$\mathrm{FC}^{\mathrm{A}} = \begin{cases} 0, if\ time < 2008Q1 \\ \\ 1, if\ time \geq 2008Q1 \end{cases}$$

The specification of the above-mentioned dummy was not only based on our identification assumption but it was also based on some past relative literature which supports that the beginning of the financial crisis in Europe was the year 2008 (Ivashina, and Scharfstein, 2010; Lane, 2012; Demirguc Kunt *et. al.*, 2013; Gibson *et. al.*, 2016). We are aware that the 2008 financial crisis did not last until 2016Q1 for all Euro area economies, since an anemic recovery started in 2014 for the majority of them. However, in order to capture even the extreme case of Greece, we define the crisis dummy to last until the end of the sample following Anastasiou *et. al.* (2019).

Apart from the two main financial crisis variables that we examine, we also include a set of macroeconomic-control variables, which are briefly discussed below:

UNEMP denotes the unemployment rate. A higher unemployment rate may result in more firms being unable to meet their debt obligations and hence senior bank loan officers tighten their CS. Thus, we expect a positive sign.

LTGBY stands for long-term government bond yields. A country with a higher long-term government bond yield faces a greater risk of default and thus banks are getting more conservative for granting loans. Hence, a positive sign is expected.

---

[5] We use only English-language searches to develop an indicator proxying for the perceived financial crisis. It is conceivable that the Euro area residents might use their mother languages when they search on the internet. Nevertheless, we employ the GSVI "financial crisis" only in the English language, since it is a widely used language by the Euro area residents.

INFLRAT is inflation rate measured by the percentage change of the Consumer Price Index. A high inflation rate may lead to monetary instability and economic uncertainty, making banks more conservative. Thus, tighter CS are expected to be set by the banks. Hence, a positive sign is anticipated.

BC, BC_TREND: stand for business cycle and trend. To construct these two variables, we follow Drehmann *et. al.* (2012) and we decompose the natural logarithm of real GDP into its long-run (BC_TREND) and short-run components (BC) with the use of the Christiano-Fitzgerald filter (2003). Based on the existing literature we expect a negative association between the two components of the real GDP decomposition and CS (Anastasiou *et. al.*, 2018).

In table 3 we provide the main descriptive statistics of our explanatory variables by country.

[Insert Table 3 here]

4. Econometric methodology

Before we proceed to the main econometric methodology, we plot the path of the GSVI "financial crisis" and bank CS as averages for the whole sample (across all 14 Euro area countries of our sample).

[Insert Figure 2 here]

In general, as it can be depicted from Figure 2, there is a common path between the under examination GSVI and bank CS. This common and positive relation becomes even clearer in the post 2008 economic downturn period, implying a positive association between these two variables. As expected, CS were tighter during the outburst of the 2008 financial crisis than in the period before its eruption. Such a result is reasonable since banks in the euro area at the outbreak of the crisis became more conservative with their lending policies due to their fear of possible rising of credit risk. By contrast, after the fourth quarter of the year 2009 we observe a clear downward trend of CS that is, banks started to soften again their CS after the outburst of the crisis, while at the same time the search intensity of the GSVI "financial crisis" started to decrease.

Table 4 reports the results of two alternative unit root tests: the Augmented Dickey-Fuller (1979) and the Phillips-Perron (1988). Three of the macro-control variables that we employ are non-stationary in level and therefore they have to be expressed in first differences to include them in our model.

[Insert Table 4 here]

Given that i, t, CS, FC^P, FC^A, and MACRO denote country, time, perceived financial crisis, actual financial crisis and a set of control-macro variables respectively, we estimate the following two alternative econometric specifications:

$$CS_{i,t} = a + \beta_1 FC_{i,t}^{P} + \beta_2 FC_t^{A} + \sum_{i=1}^{5} \gamma_i MACRO_{i,t} + u_{i,t} \qquad (1a)$$

$$CS_{i,t} = a + \beta_1 FC_{i,t-1}^{P} + \beta_2 FC_t^{A} + \sum_{i=1}^{5} \gamma_i MACRO_{i,t-1} + u_{i,t} \qquad (1b)$$

In the above models, apart from the two key variables of interest (perceived and actual financial crisis), we also include a set of macroeconomic determinants as control variables. In particular:

$$\sum_{i=1}^{5} \gamma_i MACRO_{i,t} = \gamma_1 \mathrm{UNEMP}_{i,t} + \gamma_2 \mathrm{LTGBY}_{i,t} + \gamma_3 \mathrm{INFLRAT}_{i,t} + \gamma_4 \mathrm{BC}_{i,t} + \gamma_5 \mathrm{BC\_TREND}_{i,t}$$

To investigate the validity of the self-fulfilling prophecy in the case of 2008 global financial crisis, we employ the following binary choice regression model[6] :

$$\Pr(FC_t^A = 1) = F(a + \beta FC_{i,t-1}^{P} + \mu_{i,t}) \qquad (2)$$

where $\Pr(FC_t^A = 1)$ denotes the probability of being in the crisis period. In order to capture the notion of the self-fulfilling prophecy, we employ the one period lag of perceived financial crisis as explanatory variable. It should be mentioned here that in this model we do not include any other potential factors which may have contributed to the outbreak of the 2008 financial crisis in order to capture the notion of the self-fulfilling prophecy in the best possible manner.

To select the appropriate estimation methods for the above models, we have to verify whether the explanatory variables of models (1a, 1b and 2) are exogenous. To do this, we employ the Durbin-Wu-Hausman test (see Wooldridge, 2010) for endogeneity in linear models for the model (1) and the Papke and Wooldridge (2008) two-step test for PROBIT models with endogenous repressors for the model (2) respectively. For

[6] The International Monetary Fund (IMF) also estimates the probability of occurring a crisis using a PROBIT model, Edison (2003).

instruments we used the first period lagged values of the explanatory variables. Both tests showed that all variables are exogenous in both models.

Furthermore, we examine for the presence of serial correlation by applying the relevant test of Wooldridge (2010). Our results[7] reveal that the residuals of the model are serially correlated.

As a first estimation methodology, we estimate both equations 1a and 1b with the Panel Corrected Standard Errors methodology (PCSE hereafter) of Beck and Katz (1995). The PCSE approach is generally a more appropriate approach for long panel data (T>N) than pooled least squares or Fixed Effects with robust standard errors (in our case T=52 and N=14). The main benefit of the PCSE approach is that allows the error term to be correlated over i, and to be heteroskedastic as well (Cameron and Trivedi, 2010).

For the estimation of the econometric specification (2) we first employ a PROBIT regression model (Guilkey and Murphy, 1993) and then a LOGIT model for robustness. Model 2 was also estimated with the inclusion of country dummies for further robustness check.

After the estimation of our models we examine the following testable hypotheses:

For models 1a and 1b:

$$Ho: \beta_1 = \beta_2$$

Rejection of this hypothesis would suggest that we have an asymmetric impact of perceived and actual financial crisis on CS. On the contrary, if we do not reject the above hypothesis then we could infer that both perceived and actual financial crisis have the same impact on bank CS.

For model (2):

$$Ho: \beta = 0$$

The rejection of the null hypothesis would suggest that the expectations for the crisis before it occurs (i.e. the perceived crisis) accelerated the outbreak of the actual crisis. Thus, the rejection of the above hypotheses will support the idea of the self-fulfilling prophecy.

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[7] The null hypothesis for the above test is that there is no first-order serial correlation. The F-statistic found to be 50.483 denoting the non-rejection of the null hypothesis.

On a more general point, the Google index is open to alternative interpretations. For example, individuals in Greece and other southern countries may have been googling “financial crisis” in 2007, but this probably reflected their interest in events abroad (as the crisis unfolded first in the US), rather than their concern that Greece may be entering the crisis. Thus, we are aware of the fact that the leading indicator properties of the GSVI for Europe may reflect more the fact that the crisis originated outside Europe and subsequently spilled over into Europe, and less the idea of the self-fulfilling prophecy.

To go one step further, we re-estimate models 1a and 1b by employing Panel Cointegrated Econometric techniques and in particular by employing Fully Modified OLS and Dynamic OLS as alternative econometric methodologies. We do so for two reasons. First, to obtain the long-run estimated coefficients, and second as a robustness check. In order to proceed with these two econometric methodologies, first, we have to examine if our variables have any cointegration relationship. Therefore, we perform two panel cointegration tests, these of Johansen (1988) and Kao (1999). The probability values for both tests found to be equal to zero, indicating that there is a cointegration relationship between our variables.

The following sub-section provides a brief presentation of the FMOLS and the DOLS estimation methods.

4.1 Estimation of the Cointegration Relationships (Panel FMOLS and DOLS estimations)

To estimate the long-run relationship between variables there is a variety of estimators. These include within-group and between-group Fully Modified OLS (FMOLS) estimators and Dynamic OLS (DOLS) estimators. FMOLS is a non-parametric approach which deals with serial correlation issues. The FMOLS technique modifies least squares to account for serial correlation effects and test for endogeneity in the regressors that result from the existence of co-integrating relationships. DOLS is a parametric approach in which lags and leads are introduced to cope with the problem irrespectively of the order of integration and the existence or absence thereof of cointegration. The major weakness of DOLS estimator is that it does not take care of the cross-sectional heterogeneity issue. Therefore, Pedroni (2000) suggested that the

FMOLS estimator is a superior estimator that deals with the cross-sectional heterogeneity, endogeneity and serial correlation problems.

At first, in order to estimate the long-run cointegrated coefficients, we follow the FMOLS method that is appropriate for heterogeneous cointegrated panels (Pedroni, 2000). This does not have the drawbacks of the OLS method of estimation, which, as Pedroni notes, are associated with the fact that a standard panel OLS estimator is asymptotically biased and that its distribution is dependent on nuisance parameters associated with the dynamics underlying processes of variables. To eliminate the problem of bias due to the endogeneity of the regressors, Pedroni developed the group-means FMOLS estimator, by incorporating the Phillips and Hansen (1990) semi-parametric correction into the OLS estimator. The technique also accounts fully for heterogeneity in short-run dynamics as well as for fixed effects.

As a second step, we also estimate our models with DOLS in order to examine for a possible long run relationship. Stock and Watson (1993) developed the dynamic OLS (DOLS) model which allows variables to be integrated of alternative orders. Stock and Watson (1993) suggested a parametric approach for estimating long-run equilibria in systems that might comprise variables with a different order of integration but which are still cointegrated. After Monte Carlo simulations they found that DOLS is more favourable, especially in small samples. Kao and Chiang (2000), Pedroni (2004) and Mark and Sul (2003) proposed extensions of the Stock and Watson (1993) DOLS estimator to panel data settings. Panel DOLS involves augmenting the panel cointegrating regression equation with cross-section specific lags and leads to the elimination of the asymptotic endogeneity and serial correlation. Pedroni (2004) has suggested a between-dimension, group-means panel DOLS estimator that incorporates corrections for endogeneity and serial correlation parametrically. Mark and Sul (2003) have established a new type of DOLS estimator which permits simultaneous dependence between cross-sectional and time series. Pursuant to them, the possible endogeneity can be eliminated by projecting the residuals into the appropriate lags and leads. Last but not least, Kao and Chiang (2000) found that DOLS estimator is both asymptotically unbiased and normally distributed, even in the presence of regressors which are endogenous.

5. Estimation results

Table 5 presents the estimation coefficients with their corresponding cluster robust standard errors for the first two models (that is, 1a and 1b) with the PCSE approach. Both types of financial crisis that we employ have the expected sign and a great impact on CS. Specifically, we find significant evidence that both the perceived and the actual 2008 financial crisis affected bank loan officers’ responses regarding bank CS in a positive manner. By this we mean that both the outburst of the 2008 financial crisis and the outburst of searching the word “financial crisis” in Google site led bank loan officers to tighten the CS of their banks. In other words, regarding the results of the perceived financial crisis, we could say that as the Google searches of the term “financial crisis” increase the greater the so-called crisis sentiment becomes and hence bank loan officers become more conservative regarding their lending policies.

Concerning the investigation of the impact of the actual financial crisis on CS our results are in line with these of Ivashina and Scharfstein (2010), Campello *et. al.*, (2010), Cornett *et. al.*, (2011), Hristov *et. al.*, (2012), and Gampetti and Musso (2016) who also found that the 2008 financial crisis had large effects on banks' lending conditions.

These results provide evidence that not only bank loan officers’ responses for CS were influenced by the general financial conditions and the general crisis sentiment that existed but also that firms' access to credit was probably affected by such changes. Given both the existing perceived and actual general pessimistic economic environment and the fact that banks tightened their CS in the period under examination, this resulted in firms having lower access to bank credit[8].

Concerning the results of the first testable hypothesis of the symmetry of the impacts, we reject it implying that perceived and actual financial crisis do not have the same impact on bank CS. By testing which of the two crisis-variables affected mostly CS, we find that the actual financial crisis had the greatest impact on them.

With respect to the estimation results from the FMOLS/DOLS econometric methodologies, we find once again results which are compatible with our previous findings. In particular, we find that the long-run estimated coefficients of both perceived

[8] As supported by Popov and Udell (2012), during the 2008 financial crisis firms were more credit constrained than the period before the crisis and especially the firms which were dealing with low equity and Tier 1 capital banks.

and actual economic crisis significantly affect bank CS in a positive manner. This finding suggests that the positive relationship between bank CS and financial crises (both actual and perceived) will retain its significance not only in the short run but in the long run as well. Thus, our results are robust to alternative econometric specifications. Moreover, this result indicates that the 2008 financial crisis had a long-lasting and not only a transitory impact on the long-run bank CSs trajectory.

[Insert Table 5 here]

Concerning the macroeconomic determinants that we utilize as control variables, we find that the vast majority of them do not have any impact on bank CS. Variables BC and BC_TREND are the only worth-mentioning control variables, being statistically significant and with the proper sign across almost all the employed econometric methodologies. Specifically, we find strong evidence that the short-run component of the real GDP decomposition (that is, the BC) along with the corresponding long-run component (that is, the BC_TREND) negatively influence the bank loan officers' responses regarding bank CS, implying that countries with the worst macroeconomic conditions (denoting by the downward phase of the BC and the downward trend of BC_TREND) tighten CS more than the others. These results provide further support to the study of Anastasiou *et. al.,* (2018).

Concerning the results of model (2), Table 6 presents the estimation coefficients with their corresponding cluster robust standard errors for both the panel PROBIT and LOGIT. Since the coefficients from the MLE do not have a direct economic interpretation, we present the marginal effects instead. The marginal effect denotes that the predicted probability of the actual financial crisis is 0.048 under the PROBIT and 0.114 under the LOGIT econometric specification. The above results are strengthened by the inclusion of country dummies providing support to our priors. In other words, we find some evidence that the expectations of the crisis, as implied by the perceived crisis, redounded to the outbreak of the actual crisis. It has to be mentioned here that our results do not indicate that the recent financial crisis erupted due to the existence of a self-fulfilling prophecy. Instead, we find that the self-fulfilling prophecy is one of the many drivers which led to the outbreak of the 2008 economic crisis.

[Insert Table 6 here]

5.1 Sensitivity analysis

Alternative Approach for the Estimation of the Perceived Financial Crisis

As we have discussed so far, the GSVI "financial crisis" captures the negative sentiment of economic agents and therefore of senior bank loan officers as well. Higher Google searches of that search term reveal a higher crisis sentiment. Hence, there is a positive association between CS and this crisis sentiment indicator.

In this section, we investigate an alternative approach to capturing the generalized perceived crisis environment. A different way to measure the expectations of economic agents in the euro area is through the European Economic Sentiment Indicator (ESI). The ESI is a survey-based indicator that aims to get insight into the beliefs of economic agents, both from the demand and the supply side of the economy. It is published on a monthly basis by the European Commission. Past empirical research finds that the ESI for the EU, the Michigan Survey for the US and other sentiment indices comprise useful information that is not already mirrored in other macroeconomic variables (see, among others, Acemoglu and Scott, 1994; Carroll *et. al.*, 1994; Bachmann and Sims, 2012; Barsky and Sims, 2012).

ESI by construction is a much more general indicator able to capture a wider range of crisis sentiment in the euro area and thus it is also able to capture the perceived financial crisis. Thus, as a first robustness check we re-estimate models 1a and 1b by employing now the ESI as an alternative indicator for the quantification of the perceived financial crisis. A higher ESI implies that economic agents have boosted their confidence about the general economic environment and as a consequence, will tend to ease the bank CS. Therefore, a negative association between CS and ESI is expected.

According to the results reported at Table 7, our previous findings remain robust even when we alter the proxy for crisis sentiment.

[Insert Table 7 here]

Exploring the impact of additional variables

To mitigate further any concerns about omitted variable bias, we consider some additional country-level variables that may have an impact on both CS (models 1a and 1b) and the actual financial crisis (model 2). Particularly, concerning the first two models we include some additional control variables as determinants which denote the aggregate (by country) banking environment[9]. In particular, we consider the following aggregate bank-specific variables: (i) Return on Assets (ROA), (ii) Loans to Deposits ratio (LTD), (iii) the logarithmic transformation of the aggregate bank total assets (SIZE), (iv) the ratio of total Non-Performing loans to total loans % (NPLS) and (v) the ratio total bank debt to total bank equity (LEVERAGE). For model 2, apart from the five previously mentioned aggregate bank specific variables, we also control for the five macroeconomic variables that we previously employed in models 1a and 1b. Our results remain robust despite the inclusion of these variables in all the regressions (see Table 8). Specifically, we find for all of our models that the two main variables under examination retain their significant sign both in the short and in the long run.

Concerning model 2, we find some additional variables which might have constituted to the outburst of the recent financial crisis, apart from the self-fulfilling notion (which is confirmed once again).In particular, we find that countries with higher NPLS and a higher unemployment rate have an increased probability of being in the crisis period, while countries with a robust banking system (denoted by higher levels of ROA and SIZE) have lower chances of getting involved into the crisis period.

[Insert Table 8 here]

Investigating the role of the enlargement of the Euro area membership

The euro area consists of nineteen member states, the first eleven of them (that is, Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal and Spain) became members on 1 January 1999. Then, Greece joined the Eurozone on 1 January 2001. Subsequently, the following seven countries also joined the Euro area on 1 January in the cited year: Slovenia (2007), Cyprus (2008), Malta (2008), Slovakia (2009), Estonia (2011), Latvia (2014) and Lithuania (2015).

We include a dummy variable (ENLARGEMENT) attaining 0 for the old- and 1 for the new-entrants in the Euro area respectively. By doing so, we set out to investigate the association between the enlargement of the European Monetary Union (EMU) and bank CS. The enlargement of the euro area could possibly have driven senior bank loan officers' decisions to ease the CS due to the existence of a general healthy economic

[9] The aggregate bank level data by country were obtained from the DataStream Database.

environment. According to a report by the European Commission (2009)[10], the enlargement fostered the new member states giving rise to a faster economic growth that allowed them to increase the GDP per capita from 40% of the EU-15 average prior to enlargement to 52% in 2008. Due to this positive role of the EU enlargement a negative sign is expected.

Table 9 presents the estimation results for the augmented econometric specifications. The lending standards seem to have been relaxed by the enlargement of the EMU under all econometric methodologies. However, the impact of the enlargement is found to be economically significant only under the PCSE approach. In any case, our results for each estimation methodology remain robust in all regression models despite the inclusion of the ENLARGEMENT variable.

[Insert Table 9 here]

6. Concluding remarks

Our results indicate that both actual and perceived financial crisis (or crisis sentiment) influence bank loan officers' decisions whether to tighten their bank CS or not. Hence, Google search-based indices might serve as valuable real-time supplements for the conduct of economic policy. Moreover, regarding the symmetry of impacts between perceived and actual financial crisis, we found that the actual financial crisis had the greatest impact on bank CS.

Although Internet search volume data could be a relatively good method of gauging the active knowledge information recovery of the general population and hence of the bank loan officers in several countries, we cannot infer though that the actual level of knowledge about the financial crisis is higher or lower, when the GSVI "financial crisis" is higher or lower respectively. Moreover, the interest in the GSVI "financial crisis" might be low in Google because some of the people who searched the search term "financial crisis" used alternative online search engines to learn more about it. On the contrary, the search term "financial crisis" could be high, simply because media coverage spreads this word. Hence, we are aware that the GSVI "financial crisis" which we used in order to capture the perceived crisis is only just a proxy for simple

[10] European Commission (2009), "Five Years of an Enlarged EU: Economic Achievements and Challenges".

awareness in the euro area and does not represent the vast majority of internet users (including the bank loan officers).

Finally, we document some evidence that the public expectations for the crisis, as implied by the perceived crisis, have contributed to the actual crisis, a fact which is in accordance with the self-fulfilling prophecy notion. Despite the fact that the PROBIT model that we employ is relatively simple and thus might prohibit us to have definitive conclusions regarding the occurrence of a “self-fulfilling prophecy effect”, this research study offers a further understanding of this issue. The peril of the self-fulfilling prophecy, as it is created by the adverse public expectations (expressed by Google searches), should be taken into consideration by the senior bank loan officers when they design and conduct their lending policies.

Conducting numerous robustness checks we can infer that our baseline results are robust to alternative econometric specifications since they retain their significance.

In terms of future research, our work could be extended in many different ways. Firstly, a more generalized perceived crisis sentiment indicator could be implemented or constructed to capture a wider range of the general population. Also, additional econometric methodologies and/or further control variables could be examined. Furthermore, the impact of both perceived and actual financial crisis could also be examined on alternative facets of banks’ performance such as on deposit flows, banks’ stock performance, liquidity ratios etc. Finally, a micro-level analysis can be conducted, examining how the two types of financial crisis we employed affect senior bank loan officers’ decision for CS for each type of firm size (that is micro, small, medium, and large). Such a micro-level analysis could shed more light on the issue at hand.

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Tables

Table 1: Descriptive Statistics by country-Credit Standards			
Countries	**min**	**max**	**mean**
Austria	-20	60	7.530
Belgium	-38	50	-0.295
Cyprus	-19	50	10.387
Estonia	-17	50	6.571
Germany	-15	45	4.153
Greece	-7	50	12.653
Ireland	-14	42	5.489
Italy	-19	80	10.255
Latvia	-20	50	8.175
Lithuania	-21	70	14.091
Luxembourg	-20	80	14.41
Portugal	-30	10	-4.375
Slovenia	-10	10	1.250
Spain	-13	60	9.755
Whole Sample-Average	-7	50	7.146

Table 2: Definition and expected sign of explanatory variables			
Variable	**Definition**	**Expected sign**	**Source**
FC^P	Perceived Financial Crisis	(+)	GOOGLE TRENDS
FC^A	Actual Financial Crisis	(+)	OWN ESTIMATIONS
UNEMP	Unemployment Rate	(+)	EUROSTAT
LTGBY	Long Term Government Bond Yield	(+)	DATASTREAM
INFLRAT	Inflation Rate	(+)	EUROSTAT
BC	Business Cycle	(-)	EUROSTAT/OWN ESTIMATIONS
BC_TREND	GDP Growth Trend	(-)	EUROSTAT/OWN ESTIMATIONS

Table 3: Descriptive Statistics by country-Explanatory variables

COUNTRIES	STATISTICS	FC^P	UNEMP	LTGBY	INFLRAT	BC	BC_TREND
Austria	**min**	0	3.9	0.45	-0.066	-1.350	3.590
	max	74	6.033	4.503	3.8	7.771	12.584
	mean	15.482	5.16	3.026	1.959	0.340	10.863
Belgium	**min**	0	5.5	0.583	-1.166	-1.354	3.599
	max	59	8.866	4.756	5.7	7.911	12.808
	mean	13.074	7.89	3.25	1.986	0.347	11.057
Cyprus	**min**	0	3.466	4.003	-1.6	-0.987	2.691
	max	78	17.633	7	5.2	5.731	9.360
	mean	19.394	8.456	5.337	1.772	0.25	8.137
Estonia	**min**	0	3.2	0.303	-2.033	-0.950	3.114
	max	56	19.2	8.553	11.5	5.423	9.285
	mean	12.524	8.61	5.276	3.771	0.238	8.024
Germany	**min**	1	5.3	0.22	-0.4	-1.626	4.172
	max	66	11.166	4.34	3.233	9.383	15.051
	mean	12.156	8.561	2.686	1.603	0.410	12.977
Greece	**min**	0	3.9	-0.1233	-1.933	-1.337	3.111
	max	80	25.7	25.993	5.433	7.628	12.149
	mean	19.163	9.776	7.118	2.185	0.333	10.507
Ireland	**min**	0	4.2	2.88	-2.766	-1.303	3.526
	max	70	15.1	10.62	3.666	7.541	11.984
	mean	20.108	7.872	4.733	1.241	0.327	10.409
Italy	**min**	0	5.9	0.43	-0.333	-1.555	3.889
	max	51	13.766	6.3	4.1	9.030	14.410
	mean	13.183	8.372	3.797	1.793	0.396	12.493
Latvia	**min**	0	5.233	1.286	-3.7	-1.02	3.186
	max	41	21.233	13.753	17.233	5.579	9.448
	mean	9.877	11.853	5.272	4.431	0.244	8.245
Lithuania	**min**	0	4.066	0.136	-1.1	-1.068	3.295
	max	37	18.2	14.5	12.30	5.914	9.964
	mean	9.088	10.163	4.648	3.242	0.259	8.624
Luxembourg	**min**	0	3.8	0.31	-1.333	-1.068	3.228
	max	62	14	4.923	5.3	6.198	10.375
	mean	12.183	7.231	3.13	2.302	0.272	8.926
Portugal	**min**	0	4.8	2.32	-1.533	-1.299	2.943
	max	50	11.3	12.94	3.8	7.464	11.912
	mean	10.414	8.661	4.928	1.552	0.299	9.567
Slovenia	**min**	0	4.133	0.406	-0.8	-1.112	2.943
	max	34	15.266	6.7	6.633	6.260	10.132
	mean	9.095	10.159	3.441	1.948	0.272	8.796
Spain	**min**	0	6.2	0.723	-0.966	-1.489	3.823
	max	67	11.2	6.513	4.933	8.666	13.911
	mean	13.653	8.778	3.711	1.919	0.379	12.080
Whole Sample-Average	**min**	0	3.2	-0.123	-3.7	-1.626	2.691
	max	80	25.7	25.993	17.233	9.383	15.051
	mean	13.605	8.683	4.284	2.265	0.312	10.050

Table 4: Unit Roots Tests				
	Fisher type ADF test		Fisher type PP test	
Variables	statistic	p-value	statistic	p-value
CS	-5.756	0.000	-7.178	0.000
FC^P	-10.363	0.000	-14.514	0.000
UNEMP	-0.598	0.274	1.178	0.880
LTGBY	-0.836	0.202	0.140	0.556
INFLRAT	-0.322	0.312	1.721	0.913
BC	-27.067	0.000	-11.855	0.000
BC_TREND	-27.232	0.000	-11.907	0.000

Notes: (a) ADF and PP denotes the Augmented Dickey-Fuller (1979) and the Phillips-Perron (1988) Unit Root Tests, respectively. (b) The null hypothesis for both tests is that there is unit root. (b) One period lag has been chosen to perform each test.

Table 5: Estimation Results for model 1						
	Short run regressions		**Long run cointegration regressions**			
	PCSE		**FMOLS**		**DOLS**	
VARIABLES	**Model 1a**	**Model 1b**	**Model 1a**	**Model 1b**	**Model 1a**	**Model 1b**
FC^A	**6.258*** (2.144)**	**5.444** (2.323)**	**8.010*** (2.374)**	**6.644** (2.765)**	**6.868* (3.614)**	**5.327* (3.115)**
FC^P	**0. 385*** (0.063)**	**0.311*** (0.065)**	**0.353*** (0.073)**	**0.287*** (0.085)**	**0.412*** (0.131)**	**0.326** (0.132)**
UNEMP	0.497 (0.535)	-0.805 (0.764)	0.0441 (1.065)	-0.806 (1.240)	0.876 (2.310)	0.157 (2.321)
LTGBY	0.147 (0.671)	0.243 (0.891)	0.587 (0.943)	0.316 (1.107)	0.635 (2.441)	-0.610 (2.415)
INFLRAT	1.265** (0.524)	0.788 (0.716)	0.565 (1.083)	0.772 (1.245)	-1.049 (2.558)	-1.900 (2.433)
BC	-2.178*** (0. 523)	-2.084*** (0.581)	-2.355*** (0.776)	-2.009** (0.904)	-2.562* (1.366)	-1.660 (1.366)
BC_TREND	-0.580*** (0.162)	-0.596*** (0.167)	-0.691 (0.583)	-0.608 (0.682)	-0.445 (0.691)	-0.514 (0.694)
Constant	8.130 (5.177)	6.588** (2.709)	4.904 (6.913)	6.015 (8.064)	2.380 (8.424)	5.162 (8.419)
Observations	950	934	949	933	945	929
R^2	0.178	0.131	0.022	0.006	0.300	0.299
Hypothesis testing (p-values)						
$\beta_1=\beta_2$	0.006	0.028	0.001	0.023	0.079	0.017

Notes: (a) *, **, *** denote statistical significance at the 10, 5, and 1 percent level respectively, (b) numbers in parentheses denote cluster robust standard errors.

Table 6: Estimation Results for model 2				
VARIABLES	**PROBIT**		**LOGIT**	
FC^P	**0.048*** (0.003)**	**0.054*** (0.004)**	**0.114*** (0.010)**	**0.127** (0.011)**
Constant	-0.075 (0. 057)	-0.194 (0.150)	-0.390*** (0.104)	-0.721** (0.262)
Country Dummies	Not Included	Included	Not Included	Included
Observations	1,248	1,248	1,248	1,248
Log (pseudo)likelihood	-677.793	-668.367	-658.356	-647.11

Notes: (a) *, **, *** denote statistical significance at the 10, 5, and 1 percent level respectively, (b) numbers in parentheses denote cluster-robust standard errors, (c) variable FC^P is expressed into one period lag.

Table 7: Robustness Checks – Employing ESI instead of FC^P as an indicator for public sentiment

VARIABLES	PCSE		FMOLS		DOLS		PROBIT	LOGIT
	Model 1a	**Model 1b**	**Model 1a**	**Model 1b**	**Model 1a**	**Model 1b**	**Model 2**	
FC^A	**2.585* (1.601)**	**5.300** (2.251)**	**3.166*** (1.125)**	**5.924** (2.322)**	**4.017 (3.034)**	**3.597 (3.301)**	-	-
ESI	**-0.723*** (0.098)**	**-0.491*** (0.119)**	**-0.717*** (0.089)**	**-0.490*** (0.096)**	**-0.606*** (0.142)**	**-0.562*** (0.151)**	**-0.121*** (0.007)**	**-0.042*** (0.015)**
UNEMP	-0.497 (0.676)	-1.356* (0.727)	-0.307 (0.854)	-1.205 (0.922)	-0.764 (1.758)	-1.475 (1.896)	-	-
LTGBY	0.503 (0.665)	0.232 (0.693)	0.515 (0.817)	0.305 (0.891)	1.220 (1.992)	-0.075 (2.112)	-	-
INFLRAT	0.941 (0.725)	0.898 (0.722)	0.752 (0.856)	0.844 (0.917)	-0.637 (1.952)	-1.046 (1.991)	-	-
BC	-1.992*** (0.709)	-2.047** (0.840)	-2.058*** (0.650)	-1.996*** (0.702)	-2.299** (1.082)	-2.261* (1.155)	-	-
BC_TREND	-0.825** (0.357)	-0.756** (0.374)	-0.869* (0.470)	-0.752 (0.511)	-0.803 (0.516)	-0.848 (0.555)	-	-
Constant	86.350*** (11.11)	60.920*** (13.40)	85.847*** (11.064)	60.266*** (11.895)	73.736*** (16.439)	70.134*** (17.630)	1.272*** (0.076)	0.864*** (0.061)
Country Dummies	Included	Included	Not Included	Not Included	Not Included	Not Included	Not Included	Not Included
Log (pseudo)likelihood	-	-	-	-	-	-	-588.178	-797.422
Observations	1,008	992	1,007	991	1,003	987	1,344	1,316
R^2	0.240	0.164	0.031	0.001	0.315	0.301	-	-
Hypothesis testing (p-values)								
$\beta_1=\beta_2$	0.197	0.071	0.062	0.005	0.017	0.195	-	-

Notes: (a) *, **, *** denote statistical significance at the 10, 5, and 1 percent level respectively. (b) numbers in parentheses stand for standard errors, (c) In the binary choice model, variable ESI is expressed into one period lag.

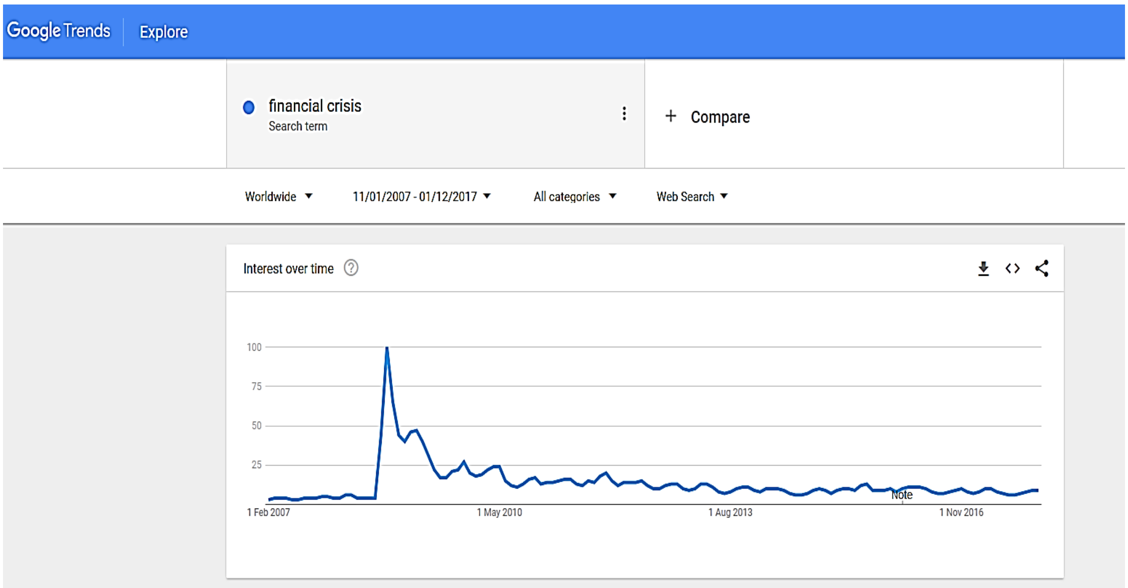
Table 8: Robustness Checks - Controlling for aggregate Bank-Specific Variables								
VARIABLES	**PCSE**		**FMOLS**		**DOLS**		**PROBIT**	**LOGIT**
	Model 1a	**Model 1b**	**Model 1a**	**Model 1b**	**Model 1a**	**Model 2**	**Model 2**	
FC^A	**6.909** **(3.134)**	**8.476** **(3.575)**	**9.713***** **(2.603)**	**10.440***** **(3.120)**	**10.410** **(4.231)**	**14.830***** **(3.854)**	-	-
FC^P	**0.384***** **(0.094)**	**0.216** **(0.105)**	**0.372***** **(0.084)**	**0.222** **(0.099)**	**0.417***** **(0.164)**	**0.167** **(0.140)**	**0.054***** **(0.00569)**	**0.132***** **(0.0141)**
UNEMP	-1.177 (1.126)	-2.070* (1.185)	-1.445 (1.396)	-2.260 (1.651)	-4.658 (3.115)	5.690** (2.848)	0.182*** (0.067)	0.350** (0.150)
LTGBY	0.392 (0.706)	0.415 (0.709)	0.447 (0.957)	0.501 (1.142)	0.616 (2.418)	0.597 (2.216)	-0.041 (0.049)	-0.067 (0.083)
INFLRAT	1.891** (0.866)	2.059** (0.884)	1.987 (1.233)	1.980 (1.450)	2.311 (2.713)	2.954 (2.380)	-0.128** (0.063)	-0.207* (0.112)
BC	-1.641 (1.776)	-1.023 (2.037)	-1.913 (1.623)	-2.236 (1.915)	-1.285 (3.183)	-2.161 (2.840)	-0.004 (0.094)	0.015 (0.162)
BC_TREND	-0.947 (0.584)	-0.647 (0.577)	-1.297 (0.812)	-1.387 (0.953)	-1.078 (0.943)	-0.863 (0.841)	-0.040 (0.062)	-0.088 (0.104)
ROA	0.302 (0.974)	-0.379 (1.020)	0.0922 (1.414)	-0.563 (1.670)	2.674 (4.430)	0.342 (4.049)	-0.178* (0.0955)	-0.349** (0.165)
LTD	-15.10*** (4.831)	-6.117 (5.285)	1.861** (0.765)	-9.105 (9.070)	6.550*** (2.09)	3.712** (1.812)	-0.436 (0.451)	-0.794 (0.794)
SIZE	14.22 (13.840)	8.845 (14.240)	2.355 (1.593)	1.591 (1.839)	1.199** (0.472)	1.464*** (0.399)	-4.034*** (0.871)	-6.390*** (1.506)
NPLS	0.204 (0.540)	0.478 (0.520)	0.249 (0.609)	0.521 (0.693)	0.650 (2.060)	0.831 (1.738)	0.120*** (0.035)	0.193*** (0.062)
LEVERAGE	0.0001 (0.0001)	0.001*** (0.001)	0.0005 (0.0006)	0.001 (0.0008)	0.0008 (0.001)	0.0006 (0.0009)	-4.86e-05 (4.06e-05)	-6.49e-05 (7.07e-05)
Constant	8.507 (7.119)	5.322 (7.115)	1.05 (0.988)	12.17 (11.640)	5.062 (12.410)	2.578 (10.940)	0.420 (0.705)	0.549 (1.177)
Observations	648	654	647	653	643	649	776	776
R^2	0.212	0.151	0.128	0.044	0.487	0.502	-	-
Hypothesis testing (p-values)								
$\beta_1=\beta_2$	0.039	0.022	0.000	0.000	0.020	0.000	-	-

Notes: (a) *, **, *** denote statistical significance at the 10, 5, and 1 percent level respectively, (b) numbers in parentheses denote cluster robust standard errors. (c) In the binary choice model, variable ESI is expressed into one period lag.

Table 9: Robustness Results: Controlling for the role of the enlargement of the Euro area membership						
VARIABLES	**PCSE**		**FMOLS**		**DOLS**	
	Model 1a	**Model 1b**	**Model 1a**	**Model 1b**	**Model 1a**	**Model 1b**
$\mathbf{FC^A}$	**6.029*** (2.124)**	**7.371*** (2.419)**	**7.460*** (2.187)**	**7.995*** (2.481)**	**6.331* (3.429)**	**6.391* (3.485)**
$\mathbf{FC^P}$	**0.398*** (0.0637)**	**0.309*** (0.068)**	**0.377*** (0.068)**	**0.298*** (0.075)**	**0.440*** (0.126)**	**0.359*** (0.125)**
UNEMP	-0.095 (0.787)	-0.823 (0.799)	0.0450 (0.978)	-0.812 (1.097)	0.952 (2.178)	0.019 (2.192)
LTGBY	0.562 (0.914)	0.258 (0.932)	0.636 (0.867)	0.339 (0.982)	0.775 (2.300)	-0.450 (2.270)
INFLRAT	0.814 (0.735)	0.893 (0.752)	0.684 (0.995)	0.901 (1.106)	-0.864 (2.414)	-1.638 (2.287)
BC	-1.362** (0.608)	-1.253** (0.621)	-1.467 (0.948)	-1.222 (1.071)	-1.622 (1.536)	-1.302 (1.533)
BC_TREND	0.224 (0.339)	0.307 (0.300)	0.229 (0.817)	4.187 (3.584)	0.400 (0.992)	0.375 (0.999)
ENLARGEMENT	-4.133*** (1.759)	-4.350*** (1.770)	-4.652 (3.170)	-0.207 (0.924)	-4.381 (3.833)	-4.361 (3.859)
Constant	-5.086 (4.504)	-5.785 (4.433)	-6.129 (9.821)	-5.092 (11.110)	-7.921 (12.12)	-6.714 (12.20)
Observations	950	934	949	933	945	929
R^2	0.183	0.150	0.004	0.017	0.305	0.304
Hypothesis testing (p-values)						
$\beta_1=\beta_2$	0.008	0.003	0.001	0.002	0.091	0.089
Notes: (a) *, **, *** denote statistical significance at the 10, 5, and 1 percent level respectively, (b) numbers in parentheses denote cluster robust standard errors.						

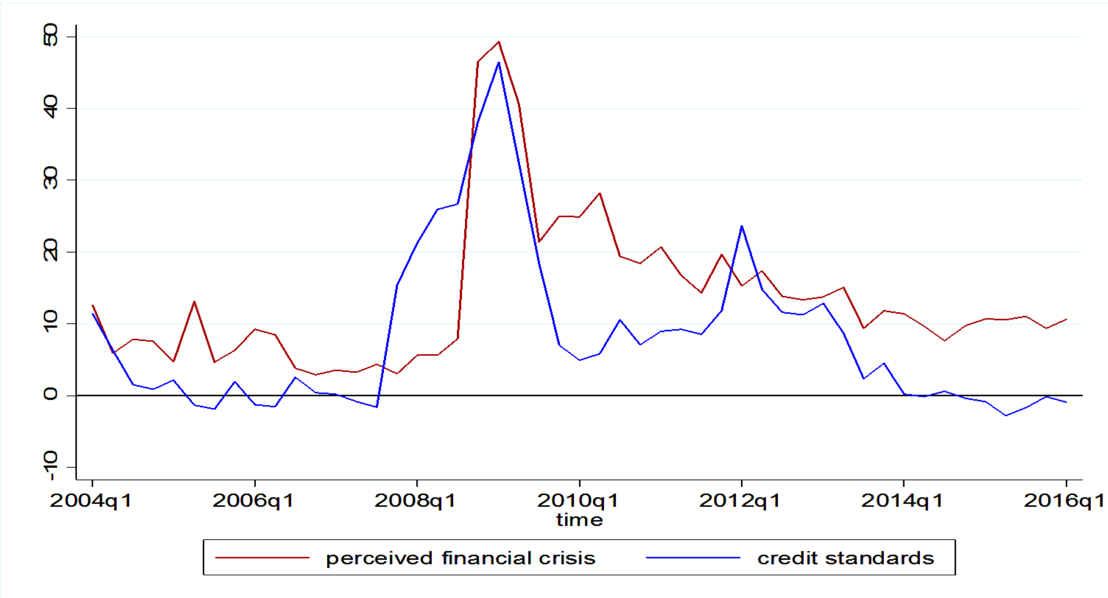
Figures

Figure 1: Illustration of the Google Trends Database



Source: Google Trends

Figure 2: Trajectory of the Google Search Volume Index "financial crisis" and bank Credit Standards - Average for the whole sample



Source: BLS, Google Trends, Own Estimations

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