RADBOUD UNIVERSITY
Nijmegen School of Management
Master Thesis

The two-way relationship between credit and stock prices in periods of bubbles and non-bubbles.

By NICK BENS (S4806360).

The credit crisis has one again demonstrated that credit fuelled price bubbles cause huge risks to the economy. This study analyses the relationship between credit and stock prices in a whole sample and bubbles, in panel and country individual analyses. The results indicate a relationship from credit to stock prices, with a positive feedback loop in credit bubbles. However, the relationship, with and without bubbles, can differ between countries.

Supervisor: Dr. Sascha Füllbrunn
Department of Economics
Master: Economics (Financial Economics)

Summary

Converging credit and price bubbles can no longer be ignored in economical thinking, as they possess great risks for the economy. Previous literatures have focussed on the relationship between credit and prices and now start to analyse their relationship in bubbles. For stock prices, the results on the relationship with credit are mixed; some studies indicate a two-way relationship, while others indicate just a one-way relationship. In addition, the relationship between stock prices and credit in bubbles has not been properly analysed yet.

This study analyses the two-way relationship between stock prices and credit. In addition, this relationship is analysed in bubble and non-bubble periods. To do so, this study uses both panel and country individual VEC and VAR models. In comparison to previous studies, this study uses different panel estimators and includes interaction variables to analyse the relationship in bubble periods. To measure bubbles, operationalizations from previous studies are used that analyse bubbles in credit and house or asset prices. The sample of interest contains quarterly data from 1980 to 2016 of eight countries.

The results indicate a relationship from credit to stock prices in the whole sample. In credit bubbles and twin bubbles, the results suggest a relationship from credit to stock prices. Moreover, in credit bubbles, the results suggest a relationship from stock prices to credit. Thus indicating a two-way relationship between the variables in credit bubbles. In addition, a relationship from stock prices to credit has little support for other bubbles. This indicates that the relationship between stock prices and credit differs between the different bubble periods. Moreover, the individual country analyses indicate that this relationship also differs across countries, which can explain a lot of the contradictions in previous studies.

Thereby, this study adds to our understanding of the relationship between credit and stock prices and to a better understanding of bubbles. This is relevant for all actors involved in the economy, as bubbles possess great risks for an economy. However, how one should restrain bubbles is less straightforward. In fact, this might not even be possible.

Table of Content

1 Introduction

In wake of recent financial crises, the causes and consequences of converging stock price and credit bubbles and their risk for an economy have been main points of attention for many policy makers and economists. A stock price bubble is a period where stock prices deviate strongly from their fundamental value. Similarly, a credit bubble is a period in which the amount of lending strongly deviates from its trend. Especially stock price bubbles fueled with credit, also referred to as leveraged bubbles, cause huge costs to an economy when the bubble collapses, as this results in many defaults on loans (Anundsen, Gerdrup, Hansen, & Kragh-sørensen, 2016; Jordà, Schularick, & Taylor, 2015). As a result, converging bubbles can no longer be dismissed as singular deviations, but have to be included in economic thinking. Now the question is how to reduce the problem of leveraged bubbles.

Before one can apply regulations to help restraining the creation and costs of stock price bubbles, one needs to know about the factors that affect price bubbles. Multiple factors have been identified that facilitate price bubbles, like lax regulation (Goodhart, Hofmann, & Segoviano, 2004), complex financial instruments (Claessens, Köse, & Terrones, 2010), excessive risk taking (Michailova, 2011) and excessive liquidity (Axelson, Jenkinson, Strömberg, & Weisbach, 2013; Guo & Huang, 2009)

One prominent factor identified is credit, as credit fueled price bubbles are the most dangerous for an economy (Jordà et al., 2015). The relationship from credit to stock prices is explained by a large amount of credit that flows to firms, either because it is cheap or expectations are high, enabling them to invest and grow, resulting in higher stock prices (Mishkin, 2008). However, at the same time it has been argued that higher stock prices encourage lending against these firms (Miao & Wang, 2011). As both theories are theoretically valid, empirical studies try to detect the direction of these relationships.

The empirical studies on the relationship between stock prices and credit find mixed results. Some studies find evidence for both a relationship from credit to stock prices and stock prices to credit, e.g. a two-way causal relationship (Goodhart, Basurto, & Hofmann, 2006; Herrera & Perry, 2001). However, other studies suggest that stock prices positively affect bank loans, but not the other way around (Almutair, 2015; Frömmel & Schmidt, 2006; Ibrahim, 2006; Kim &

Moreno, 1994; Krainer, 2014). Yet, another study suggests that credit only affects stock prices (Alshogeathri, 2011).

This study aims to explain these conflicts by studying the relationship between credit and stock prices with state-of-the-art econometric methods. In addition, this is the first study that analysis the relationship between credit and stock prices in bubble and non-bubble periods, as it is expected that bubbles affect this relationship, since it has been shown that the relationship between credit and housing prices behaves different in bubble and non-bubble periods (Shen, Lee, Wu, & Guo, 2016). The research question of this study is: *What relationship do credit and stock prices have in periods of bubbles and non-bubbles?*

The analyses are performed on a panel and individual country level. A panel error correction model (PECM) is used to examine the relationships between the two markets in the entire sample. This model is estimated using a generalized method of moment (GMM) estimator (Arellano & Bond, 1991) and a cross-country dynamic fixed effects (DFE) estimator (Pesaran, Shin, & Smith, 1999). For the individual country analysis, a vector autoregressive (VAR) model or a vector error correction (VEC) model is used. For the bubble and non-bubble analyses, it is examined whether credit, stock price and twin bubbles occur in the sample and how these bubbles affect the relationship between stock prices and credit. These analyses are also performed on a panel and country individual level using the same estimators. However, for some countries the VEC models fail to estimate the bubble and non-bubble models. For these countries, an Engle-Granger estimation is used, which is a two-step VEC model (Engle & Granger, 1987). The sample includes eight countries, seven developed countries and one emerging country, and contains quarterly data from 1980-2016. The variables included in the analyses are the stock price index and all credit to the private sector.

The results show a short-run relationship from credit to stock prices and a long-run relationship between both variables. The bubble analyses show that in credit bubbles and twin bubbles, credit positively affects stock prices in the short-run. In addition, the results show a two-way short-run relationship between stock prices and credit in credit bubbles. Thereby indicating that the relationship differs between the different bubbles. The individual country analyses show that the relationships also differ across countries, which can explain a lot of the contradictions in previous literature.

This study is organized as follows. Section 2 presents a review of the literature on the relationship between credit and stock prices. Section 3 describes the methodology, including bubble measures, panel and individual country causality models for the whole sample and bubble periods, and the data. Section 4 presents the results, including the basic statistics, panel and individual country causality models, and causality models during periods of bubbles and non-bubbles. Section 5 discusses the results. Section 6 concludes this paper.

2 Literature review

The relationship between credit and stock prices is different from the relationship between credit and property or asset prices. Between credit and property prices, researchers find a two-way relationship. This can be explained by increasing property prices that increase collateral values, which increase bank lending, which is used to finance properties and thereby enables prices to rise (Goodhart et al., 2006; Goodhart & Hofmann, 2008; Shen et al., 2016). Between credit and asset prices, one-way causality has been found from credit to asset prices. This is a result of lower discount factors, as a consequence of lower interest rates by increasing credit, which increase the present value of assets (Geanakoplos, 2010; Senhadji & Collyns, 2002). In broad terms, the theoretical explanation of the relationship between credit and stock prices also describes a two-way relationship. As increasing stock prices encourage lending against these firms, which enables them to invest, resulting in rising stock prices (Miao & Wang, 2011). This relationship is different from the two-way relationship between credit and house prices, as house prices increase collateral value, while stock prices increase expectations about the firms and their ability to repay the loan.

Yet, while the empirical studies on the relationship between credit and property or asset prices result in similar conclusion, there seem to be mixed results from the empirical studies on the relationship between credit and stock prices. Therefore, this study looks at the relationship between credit and stock prices. In the next section, the theoretical models and the empirical results on this relationship will be discussed.

2.1 Theoretical explanations of the relationships between credit and stock prices

There are two types of macro-economical models that aim to explain the relationship between credit and stock markets, which can be classified as one- and two-way models. Mishkin (2008) describes two-way causality between stock prices and credit. Stating that banks decide to increase lending because of either structural changes in financial markets or exuberant expectations about future economic performance. This credit flows to certain markets and can be invested by the firms, either because it is cheap or because expectations are high. As a consequence, performance and demand for stocks of companies in these markets increases, thereby increasing their prices. The increased stock prices encourage further lending against these firms, as they seem credit worthy, which increases demand, and thereby their stock prices even more (Mishkin, 2008). This feedback loop can generate stock price bubbles and fuel credit bubbles.

The financial instability theory also describes a two-way relationship between credit and stock prices. The relationship from credit to stock prices described is similar to Mishkin (2008), as the financial instability theory also states that increased finance bids up asset prices, which leads to increases in investment (Minsky, 1977). The financial instability theory describes three ways of financing; (1) hedge finance, in which cash flows of the investment can pay debt obligations, (2) speculative finance, in which the present value of cash flows is larger than the present value of the debt obligations, but new debt needs to be raised to fulfil the payments, and (3) Ponzi finance, in which debt payments are fulfilled by increasing the amount of debt, expecting that the appreciation of the investment will be sufficient to refinance the debt. These ways of finance are important for the relationship from stock prices to credit. In fact, stock prices have an effect on credit with Ponzi finance, because if stock prices drop, the debt cannot be repaid. The defaults on Ponzi finance and decreasing stock prices affect the willingness of lenders to lend, which restrains speculative borrowers to reroll their debt. This could then bring down hedge borrowers, who are unable to find loans despite the soundness of their investment (Minsky, 1977).

An alternative explanation for two-way causality is that changes in stock prices can indicate that the expectations of future economic activity change. This has an impact on the demand for credit. If both the borrower and the lender expect that the stock prices will be high, firms will not mind borrowing more and lenders will not mind lending more. As a result, the firms gain additional capital, which they invest to improve future production, making them indeed more valuable and encouraging further lending (Miao & Wang, 2011).

Although Mishkin's theory starts by an increase in credit and Miao and Wang's theory with changes in stock prices, both theories state that expectations about future performance initiate the two-way relationship. In addition, both theories explain a similar feedback loop of lending resulting in higher stock prices, which encourages further lending, which can increases stock prices again. Minsky (1977) supports this feedback loop, but also describes the consequences when bubbles burst.

The theories that explain just one-way causality mainly refer to one side of the two-way theories. The balance sheet effect states that as stock prices increase, the balance sheet of a firm increases. This increases the creditworthiness of a firm, and thereby their access to credit

(Bernanke, Gertler, & Gilchrist, 1999). Hence, this theory embodies the relationship from stock prices to credit explained by the two-way theories. Another theory states that stock price changes indicate changes in expectations, which can have an effect on credit (Kim & Moreno, 1994). Miao and Wang (2011) also describe this relationship in their two-way model. The leverage cycle explains that bad news in one sector could easily spread to other markets, because the pool of risk-taking capital is small in comparison to the size of the global market (Geanakoplos, 2010). This is similar to Minsky (1977), as he states that bad news for Ponzi financers could cause problems for other borrowers. However, the leverage cycle also explains that bad news does not have to start in stock markets. Due to financial contagion, it can also start in other markets.

There are two alternative one-way models that might explain anomalies of the two-way models, but are not in contrast with them. The risk shifting theory states that the causal relation from credit to stock prices starts with banks deciding to increase credit. In contrast to Mishkin (2008), investors borrow this money and invest in risky assets, such as stocks. These investments are relatively attractive to investors, because they can avoid losses in low payoff states by defaulting on the loan. This risk shifting leads to a high demand for risky stocks, while supply is fixed, which results in stock price bubbles (Allen & Gale, 2000a). With this model, there is no feedback loop, but the stock price bubbles can initiate a feedback loop described by Miao and Wang (2011). Kim and Moreno (1994) describe another channel for the relation between stock prices and credit. They state that financial institutions can hold a significant amount of stocks, especially in Japan. As a result, changes in stock prices can have a significant affect on the market value of bank equity, which plays a significant role in bank lending. However, the holding of shares by financial institutions is regulated, or even permitted, in many countries.

Besides the macro-economical models, there are also behavioral models that aim to explain the relationship between stock prices and credit. These models focus on the intrinsic motivation of investors and why investors are willing to pay higher prices. Examples are the greater-fool model (Doblas-Madrid, 2012) and agency models (Allen & Gale, 2000b; Allen & Gorton, 1993; Barlevy & Fisher, 2010). A consequence of including the intrinsic motivation of investors in these models is that it is very difficult to empirically test them. Therefore, this study excludes behavioral models and only focuses on the macro economical models.

2.2 *Empirical evidence of the relationship between credit and stock prices*

This section first lists the different studies on the relationship between credit and stock prices (Table 1). Thereafter, the possible explanations for the contrasting results and remaining gaps are discussed. The empirical results differ by the direction of causality, but also by indicating long or short-run causality. Long-run causality indicates that variables follow the same trend. While short-run causality indicates that errors from the long run are explained by the other variable (Ratanapakorn & Sharma, 2007).

Sample Region	**Two-way causality**	Method	**Credit → Stock price index**	Method	**Stock price index → Credit**	Method
Europe	Goodhart et al. (2006)	VAR & OLS			Krainer (2014) Levieuge (2014) Frömmel and Schmidt (2006)	OLS VAR MS
Asia			Alsheathri (2011)	VAR & GARCH	Almuntair (2015) Ibrahim (2006) Kim and Moreno (1994)	VAR VAR VAR
South-America	Herrera and Perry (2001)	SUR				

TABLE 1 LIST EMPIRICAL STUDIES AND THEIR FINDING ON THE RELATIONSHIP BETWEEN CREDIT AND STOCK PRICES

Notes: 1: Sample region indicates in which region the countries or panels analyzed are located. Note that different countries in Europe and Asia are studied, in panel or individual country analysis.
2. Method indicates vector autoregressive models (VAR), Seemingly Unrelated Regression (SUR), GARCH Models, Ordinary Least Squared regressions (OLS) and Markov-Switching models (MS).
3. Two-way causality is causality both from credit to stock prices and stock prices to credit.

There are two studies that indicate two-way causality between credit and stock prices. Herrera and Perry (2001) conduct a seemingly unrelated regression and find two-way causality between stock prices and credit in South America. In addition, Herrera and Perry (2001) study the relationship between credit and stock price bubbles. Using a logistic regression model, they find a positive relation between credit and stock price bubbles. The two-way relationship is also analyzed with VAR and OLS models in industrialized countries, including Germany, France, Finland and the Netherlands. This study also finds a two-way relationship between credit and stock prices (Goodhart et al., 2006).

In contrast, other studies only find a one-way relationship, either from credit to stock prices or from stock prices to credit. Alshogeathri (2011) uses a VEC model in an Indian case study and finds that credit has a long-run positive effect on stock market prices, but not in the short-run. In addition, there is no evidence for a relationship from stock prices to credit (Alshogeathri, 2011). Other studies find evidence for short-run causality from stock prices to credit in Saudi Arabia

(Almutair, 2015), Malaysia (Ibrahim, 2006) and Europe (Krainer, 2014). Thereby indicating that this relationship even holds in bank centered financial systems. In addition, these studies explicitly reject the relationship from credit to stock prices. These studies do differ as Krainer (2014) uses an ordinary leased squared regression for the analysis, while Almuntair (2015) and Ibrahim (2006) use VAR models. Other studies that use VAR models find a relationship from stock prices to credit in Japan (Kim & Moreno, 1994) and France (Levieuge, 2017), but these studies do not analyze the reverse relationship. Neither do Frömmel and Schmidt (2006), who find a relationship from stock prices to credit in Belgium, Germany, Ireland, France and the Netherlands. They do include some kind of bubbles in this analysis by studying periods of disequilibrium using a Markov-switching error correction model.

There are multiple possible explanations for these contrasting results adduced by multiple studies, which are omitted variables, country specific effects, different methods and bubble periods. Starting with an omitted variable, which can affect both stock price and credit in certain relationships. A perfect candidate that could explain the two-way relationship would be economic development. As this improves institutional systems and capital markets, which can increase both credit and stock prices (Yartey, 2008). However, other studies show that stock markets and credit can be good predictors for economic growth, while the opposite is not true (Beck & Levine, 2002; Foresti, 2006; Levine & Zervos, 1998). Moreover, the studies in Saudi Arabia (Almutair, 2015) and Malaysia (Ibrahim, 2006) explicitly reject the causal relation from credit to stock prices, while these are also emerging countries. Therefore, the finding of the relationship from credit to stock prices cannot be prescribed to the omitted variable economic development.

Country specific effects that influence the relationship between stock prices and credit can also explain the contradicting results. This can remove a lot of the contradictions, since this makes different countries not comparable (Alshogeathri, 2011; Levieuge, 2017). However, there remain some mixed results for European countries, as studies find two-way or one-way causality for these countries.

The use of different methods can explain why Goodhart et al. (2006) find a two-way relationship in France, while Krainer (2014), Levieuge (2017) and Frömmel and Schmidt (2006) only find a one-way relationship. Levieuge (2017) and Frömmel and Schmidt (2006) only analyse the relationship from stock prices to credit and ignore the reverse relation. Goodhart et al. (2006) use a VAR model for both individual country analyses and panel analyses and OLS models for additional individual country analysis. Krainer (2014) uses tests based on OLS regressions for a European panel, which can be biased for time series. However, a panel VAR model also has some limitations, as shown in section 3.1 below. In addition, Goodhart et al. (2006) also find two-way causality for the individual countries using OLS regressions. Therefore, one cannot draw conclusions on the basis of these studies.

Another explanation for the contradictions can be that the relations are different for bubble and non-bubble periods. In general, stock prices do not perfectly match credit (Drehmann, Borio, & Tsatsaronis, 2012). However, stock prices register sharper increases in periods of credit bubbles (Claessens, Kose, & Terrones, 2010) and credit growth is usually high in stock price bubbles (Christiano, Ilut, Motto, & Rostagno, 2010). In addition, experimental evidence suggests that margin purchasing, which can be considered as some sort of credit purchase, reinforces stock price bubbles (Neugebauer & Füllbrunn, 2013). Moreover, empirical evidence suggests that the relationship between housing prices and credit is differs in bubble periods (Shen et al., 2016). This suggests that the relationship might change in bubble periods. The one study that analyses causality in disequilibrium only analysis a one-way relationship from stock prices to credit, but finds causality in France, among others (Frömmel & Schmidt, 2006). However, studying disequilibria to analyze bubbles is questionable. In addition, Levieuge (2017) excludes bubbles and also finds a one-way relationship in France. Moreover, Goodhart et al. (2006) find a two-way relationship in France, excluding bubbles.

Despite these explanations, some aspects remain unclear. A contrast remains between Krainer (2014) and Goodhart et al. (2006) finding one-way causality and two-way causality for European countries. Using an alternative method can provide clearance on this contrast. In addition, there is no study that analyzes the relationship between credit and stock prices in predefined bubble periods, while previous studies indicate that bubbles can have an effect on this relationship.

2.3 Hypothesis

The first hypotheses focus on the relationship between credit and stock prices, because of the contradicting results of the empirical studies. The theoretical models suggest a positive two-way relationship between stock prices and credit. Therefore, the first two hypotheses are:

H1: Credit has a positive effect on stock market prices.

H2: Stock prices have a positive effect on credit

In addition, the theoretical models indicate that credit bubbles enable firms to grow and that stock price bubbles motivate lending. However, the effect of bubbles on the two-way relationship between stock prices and credit is not studied by previous literature. In addition, it is interesting to study if credit bubbles have an affect on the relationship from stock prices to credit, or if this relationship only holds in stock price bubbles. Moreover, it is interesting to study the two-way relationship in non-bubble periods, as the theoretical models merely indicate that the relationships start with bubbles. Therefore, the third and forth hypotheses are:

H3: Bubbles affect the relationship from credit to stock prices.

H4: Bubbles affect the relationship from stock prices to credit.

Finally, previous empirical studies provide strong evidence for differences in causality across countries. As a consequence, it is expected that the effects of bubbles on the relationship between stock prices and credit will also differ across countries. Therefore, the last two hypotheses are:

H5: The relationships between stock prices and credit can differ between countries.

H6: The effect of bubbles on the relationships between stock prices and credit can differ across countries.

3 Methodology

This chapter documents the methods to analyze the relationship between stock price and credit. Section 3.1 compares the models used in previous studies and elaborates on the application of the selected models. Section 3.2 presents the models in bubble periods. Section 3.3 describes the dataset used in this study.

3.1 Model selection

Previous literature uses different models to analyse the relationship between stock prices and credit, like a Markov-Switching model, OLS regressions, GARCH and ARCH models and individual or panel VAR and VEC models. Starting with the Markov-Switching models (Frömmel & Schmidt, 2006; Guo & Huang, 2009). These models analyze the relationship between credit and price bubbles in two different regimes, a stable and a non-stable regime, using VAR or VEC models. However, Markov-Switching refers to the probability that one regime moves to another regime and vice versa. This is difficult to implement, as the likelihood that one regime (credit bubbles) moves to another regime (stock prices bubbles) is unknown upfront.

Another model used in previous literature is an OLS regression (Krainer, 2014), combined with binary bubble dummies for a logistic regression (Herrera & Perry, 2001) or country dummies for cross-country effects studies (Kuttner, 2012). There are two limitations to such models. First, a logistic regression analyses the effect of macroeconomic variables on the probability of price bubbles. However, this model is unable to capture the relationship between the macroeconomic variables in bubbles. But more importantly, applying an OLS regression to a panel dataset results in dynamic panel bias (Roodman, 2006).

GARCH or ARCH models can also analyse a relationship between credit and stock prices (Alshogeathri, 2011). These models account for the stylized facts of stock markets, which are high volatility, tailed, non-normal distribution and asymmetric volatility, but can only be used with stationary variables. GARCH and ARCH models focus on volatility and how shocks in one variable explain volatility in another variable. This indicates a relationship, but does not prove causality. In addition, it does not make sense to analyse the relationship in bubble and non-bubble periods with this method, since the shocks can already be considered as bubbles.

At last, previous literatures use panel or individual VAR or VEC models. Both the panel and individual models analyse whether the variable of interest can be explained by the independent variables. Thereby, they do not isolate the effect of each independent variable, but they do indicate an influence and thereby causality (Guo & Huang, 2009; Kim & Moreno, 1994). However, one can argue that true causality can be analysed in empirical studies, as there is always the possibility that an omitted variable affects both of the variables. The VAR and VEC models can be used to regress a multi-period dynamic relationship with non-stationary variables with a stationary or stochastic trend (Guo & Huang, 2009). The advantage of a panel model is that it substantially increases the efficiency and power of the analysis by analysing all information in the sample in one model. In contrast, individual country level analysis could suffer from too few degrees of freedom, in particular when the models are re-estimated over a sub-sample with fewer estimations (Goodhart & Hofmann, 2008). A drawback of using panel models is that they pool information across countries and thereby disregards cross-country differences in the estimation (Goodhart & Hofmann, 2008). Goodhart and Hofmann (2008) include dummy variables in a VAR model, specifying the dummy variable to separate the countries with particularly high house price inflations and low house price inflations to get an indication about the effect of house price bubbles (Goodhart & Hofmann, 2008). It would however be more informative to include dummy variables for bubbles to analyse the relationship in bubble periods (Shen et al., 2016).

Comparing these potential models, the panel and individual VAR or VEC models are selected to test the hypothesis in this study. That is because they do not require upfront knowledge of regimes, they control for dynamic panel bias and they, as far as empirically possible, indicate causality. In addition, these models can include dummy variables for bubble periods to analyse the relationship between credit and stock prices in periods of bubbles. Assuming that the variables of interest are non-stationary and co-integrated, a panel VEC model is used to analyse the relationship on the entire sample. To analyse the country specific relationships VAR or VEC models are used, depending on whether or not the variables are co-integrated. Figure 1 presents a graphical overview of the methodology of this study.

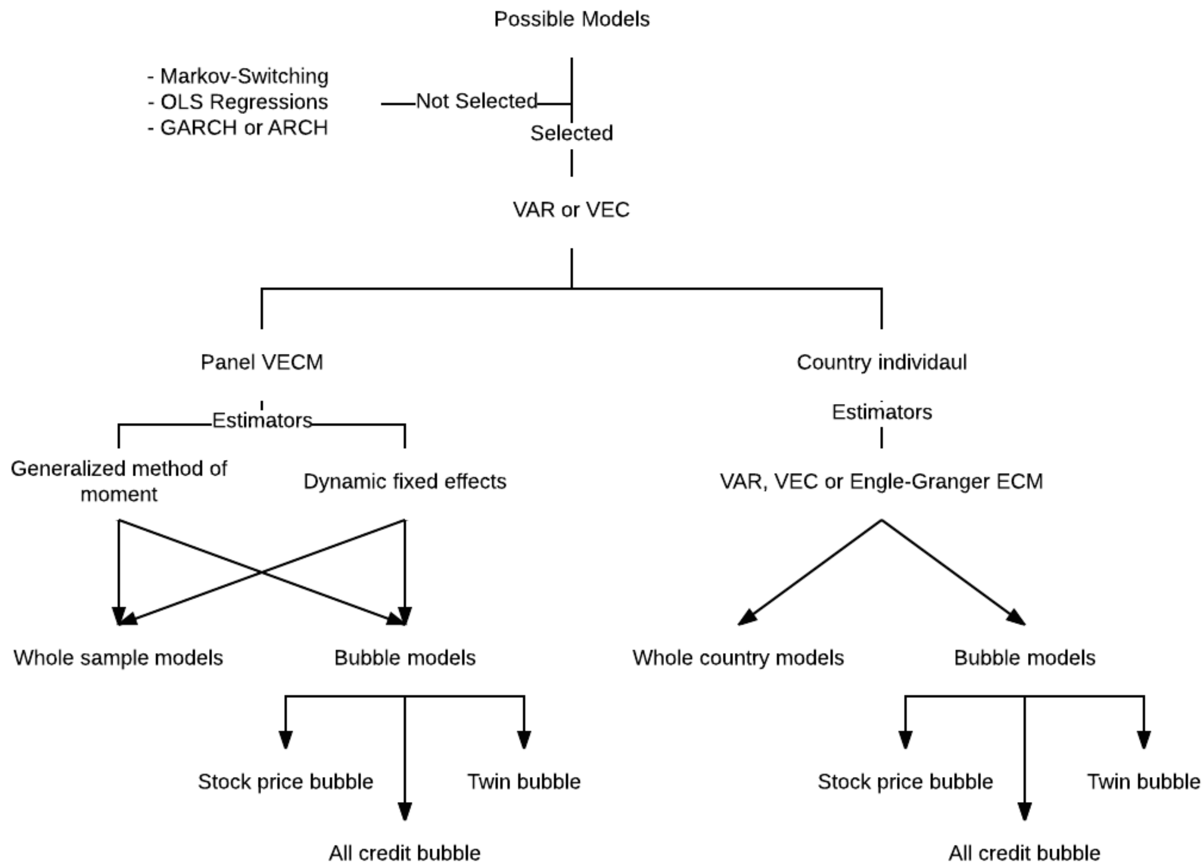


FIGURE 1 GRAPHICAL OVERVIEW OF THE METHODOLOGY

3.1.1 Panel vector error correction model

The panel VEC model is similar to the model in Shen et al. (2016), who conduct a similar analysis on the relationship between housing prices and credit. The model is specified below.

$$\Delta y_{i,t} = \alpha_{0,i} + \alpha_1 \Delta y_{i,t-1} + \alpha_2 \Delta y_{i,t-2} + \beta_1 \Delta x_{i,t-1} + \beta_2 \Delta x_{i,t-2} + \phi ECM_{i,t-1} + \varepsilon_{i,t}$$

In the equation above, y and x are representing *SPINDEX* (stock price index) and *ACREDIT* (all credit to the private sector) alternatively, depending on the model. Subscripts i and t represent the i-th country and the t-th quarter, respectively. Δ is the difference operator and ε is the error term. ECM is the error correction term; $ECM_{i,t-1} = y_{i,y-1} - \theta x_{i,t-1}$, were θ is the long-term co-integrating variable. If y and x are not co-integrated, θ will be zero, removing ECM.

The model is applied using two different estimators, starting with the generalized method of moments (GMM) estimator (Arellano & Bond, 1991). Shen et al. (2016) also use this estimator to analyse their model. The advantage of this estimator is that it is designed for situations with a single dependent variable that is dynamic and depending on its own past realizations, independent variables that are not strictly exogenous and possibly correlated with the error, fixed individual effects and autocorrelation, and heteroskedasticity within individuals, but not across them. Moreover, the estimator can include additional instruments to improve efficiency, either in first difference, level or both (Roodman, 2006). However, there are also disadvantages in using this estimator, as differencing can reduce the sample size when the data is balanced. Moreover, the estimator is designed for small-T large-N samples. In large-T samples, the number of instruments will be large too. This affects the Sargan and Hansen tests of over identification restrictions, as the validity of these tests is worrisome when the number of instruments exceeds N. In addition, small-N might lead to unreliable autocorrelation tests (Samargandi, Fidrmuc, & Ghosh, 2015).

There are several options in the original estimator to correct for these limitations. In addition, Roodman (2006) implements new options to improve the estimator. To reduce the number of instruments, one can collapse the instrument matrix. This combines the time periods of each lag in one column, instead of generating a column for each time period and lag variable (Roodman, 2006). Some information will get lost, but this improves the models efficiency if N is small. To further reduce the number of instruments, one can also restrict the number of lags included as instruments and restrict the equations for the instruments to just level of first difference variables (Roodman, 2006). This study uses all these correction, because of the small-N sample. This means that the instruments only include the second to fifth lags and either the first difference or level equation. The instruments *ACREDIT* and *SPINDEX* are included in their first differences, because changes in these variables are more informative than their real values to estimate their future values. The instrument *ECM* is included in level, because for this variable the real values are more informative. To preserve the sample size of the balanced sample, forward orthogonal deviations are used instead of first differences. This subtracts the average of all future observations (Roodman, 2006). Lastly, small-sample corrections to the estimates are used, resulting in F instead of Chi^2 tests for overall fit and t instead of z tests statistics for the coefficients. However, results from the Sargan and Hansen tests and autocorrelation test will remain worrisome.

The second estimator used in this study is the dynamic fixed effects (DFE) estimator (Samargandi et al., 2015). This estimator allows short-run coefficients to be country specific, but restricts the long-run slope coefficients and error variances to be equal across countries. However, this estimator has a cluster option that allows intra-group correlation with the error term (Blackburne & Frank, 2007). It is very likely that the residuals will be correlated across years within countries. Hence, the standard errors are clustered by country to take this error structure into account. There are two requirements for the efficiency and validity of this method (Blackburne & Frank, 2007). First, the coefficient of the error correction term should be negative, but not lower than -2.000, to support the existence of a long-run relationship between the variables of interest. Second, an important assumption is that the model can treat the explanatory variables as exogenous. This is fulfilled by including the lags of the variables of interest in the error correction term.

The models include just two lags of the variables for credit and stock prices in first difference. First differencing is used to eliminate individual effects (Shen et al., 2016). Only two lags of the explanatory variables are included and additional control variables are not considered, because of the small-N sample. This is common in panel data because the estimation consumes a notable degree of freedom (Shen et al., 2016). Multiple previous studies analyse the log first differences of the variables (Alshogeathri, 2011; Guo & Huang, 2009; Shen et al., 2016). However, one should be careful with Log variables; if they are non-stationary the results can be misleading. First differencing the variables will not solve this problem (Ibrahim, 2006). Since this study is especially interested in big spikes in the growth rate of the variables, log values are not considered.

To interpret the results and analyse causality, an F-test is used to test the following null hypothesis:

$$H_0\ (whole\ sample): \beta_1 = \beta_2 = 0$$

This hypothesis states that x does not Granger-cause y (Shen et al., 2016), which is similar to the theoretical hypothesis that credit (the stock price) does not affect the stock price (credit). This hypothesis is referred to as short-term causality, long-term causality evaluates whether $\theta > 0$ (Samargandi et al., 2015). However, this model only explains cause-effect relationships with constant conjunction. If both variables are driven by a common third variable, one can still fail to reject the alternative hypothesis.

3.1.2 Individual country models

The individual country models do not differ much from the panel VEC model, except that they focus on just one country, so they can be compared. In addition, the VAR model does not contain an error correction term. The models are specified below.

$$VEC: \Delta y_t = \alpha_0 + \alpha_1 \Delta y_{t-1} \dots + \alpha_p \Delta y_{t-p} \beta_1 \Delta x_{t-1} \dots + \beta_p \Delta x_{t-p} + \phi ECM_{t-1} + \varepsilon_t$$

$$VAR: \Delta y_t = \alpha_0 + \alpha_1 \Delta y_{t-1} \dots + \alpha_p \Delta y_{t-p} + \beta_1 \Delta x_{t-1} \dots + \beta_p \Delta x_{t-p} + \varepsilon_t$$

In both equations, y and x are representing *SPINDEX* and *ACREDIT* alternatively, depending on the model. Subscript t represents time at quarter, Δ is the difference operator and ε is the error term. ECM in the VEC model is defined as; $ECM_{t-1} = y_{y-1} - \theta x_{t-1}$, were θ is the long-term co-integrating variable. If y and x are not co-integrated, θ will be zero, removing ECM, resulting in the VAR model.

These models will be estimated using regular VAR or VEC estimations and Engle-granger error correction models (EG-ECM). In some cases, the VEC models are unable to perform the analysis as a result of collinearity problems. When this happens, the models is estimated with the two-step EG-ECM (Engle & Granger, 1987). This estimation first regresses y on a constant and lags of x to calculate the residuals. The second step regresses the first difference of y on the lagged first differences of x and the lagged level of the first-step residual. The results of this estimator are very similar to those of VEC estimations, but the two-step approach tackles the collinearity problem. All models estimate the variables in their first difference, while the number of lags included can differ across countries. This is a consequence of using Akaike Information Criterion (AIC) for each individual country to determine the number of lags.

For each country, the null hypothesis that x does not Granger-cause y is given by:

$$H_0\ (individual\ country): \beta_1 = \beta_2 \dots = \beta_p = 0$$

This hypothesis for short-term causality is evaluated by Granger-causality test, expressed by F statistics for VEC models. Long-run causality evaluates whether θ > 0 (Samargandi et al., 2015).

Similar to the panel analysis, one might incorrectly accept the alternative hypothesis if both variables are driven by a common third variable.

An impulse response function is used for a robustness check. This determines the length, direction and magnitude of the volatility of the variables in the system when affected by a shock to another variable (Alshogeathri, 2011). Innovations in VAR and VEC equations may be contemporaneously correlated. This means that a shock in one variable may work through too contemporaneous correlation with innovations in other variables. However, the models consist of only two variables, so this will not cause problems.

3.2 Bubble periods

This study also considers causality between credit and stock prices during bubble periods. In addition, the relationship is analysed when the two bubble periods coincide, defined as twin bubbles (TB). This section first defines credit and stock price bubbles and concludes with the models in bubble periods.

3.2.1 Credit bubbles

A credit bubble can be defined in two ways. One is an episode of high credit growth that is unsustainable and eventually collapses (International Moneatry Fund, 2004). A collapse means that the willingness or ability of banks to lend is reduced, stagnating credit growth (Frömmel & Schmidt, 2006). Not all growth episodes can qualify as a credit bubble. According to the International Monetary Fund (2004), high credit growth means that credit growth exceeds its median growth rate. Based on a sample of 28 emerging countries, a credit growth rate around 17% is found to be high (Mendoza & Terrones, 2008). A second definition of credit bubbles is a strong deviation from its trend (Goodhart & Hofmann, 2008), often preceded by multiple periods of high credit growth. This definition embodies bubbles that are formed by multiple periods of strong credit growth, while the first definition is a snapshot of one period.

There are slightly different operational definitions in the literature for these definitions. The first two definitions are from Shen et al. (2016). They define credit bubbles when the deviation of credit from its trend is greater than 1.5 times the standard deviation and the credit growth rate exceeds 10%. They also define bubbles as an episode when the annual growth rate of credit exceeds 15%. These two operationalizations are based on previous literature, but they are very generalized. A trend can also be defined as a Hodrik-Prescott filtered trend, which removes the cyclical component from a time series to become less sensitive to short-term fluctuations and better represent long-term fluctuations (Borio & Lowe, 2002). In addition, there are slightly different definitions for a deviation from a trend. Alternatives are a deviation of 1.75 times the standard deviation (Mendoza & Terrones, 2008), a deviation of more than 5% lasting at least 12 quarters (Borio & Lowe, 2002), or a deviation from a credit-to-GDP ratio of 24% (Gourinchas, Valdes, & Landerretche, 2001). Moreover, previous literature also uses a threshold of 20% for the credit growth ratio (Barajas, Dell' Ariccia, & Levchenko, 2007). These different operationalizations are a consequence of bubbles being very difficult to measure (Brunnermeier & Oehmke, 2012).

Considering these operationalizations, this study defines two measures of credit bubbles. Credit boom 1 (ACB1) is a period where the credit growth ratio exceeds 15%, following Shen et al. (2016). This seems a reasonable threshold, since credit growth is found to be high around 17% (Mendoza & Terrones, 2008). Credit bubble 2 (ACB2) is a deviation of credit from a Hodrick-Prescott filtered trend with more than *k* times the standard deviation, where *k* is initially set to be 1.5. A smoothing parameter of 1600 is used to have the most accurate filtered trend for quarterly data (Hodrick & Prescott, 1997). For robustness tests, different *k* values and a deviation of 5% for 12 quarters are also considered.

$$ACB1 = \begin{cases} 1 \; if \; Credit \; growth \; rate > 15\% \\ 0 \; otherwise \end{cases}$$

$$ACB2 = \begin{cases} 1 \; if \; Credit_{i,t} > \; E(Credit)_{i,t} + k * \; \sigma_i \\ 0 \; otherwise \end{cases}$$

In the equation of ACB1 above, credit growth rate is the yearly percentile change of credit to control for seasonal effects. In the equation of ACB2, Credit is the real value of credit, E(Credit) is the expected value of credit based on the Hodrick-Prescott filtered trend, *k* is assumed to be 1.5 and σ is the standard deviation of credit for the respective country.

3.2.2 Stock Price bubbles

The definitions of stock price bubbles are very similar to the definitions of credit bubbles. Hence, a stock price bubble can be defined as an episode of high stock price growth, or a strong over-pricing of a stock price from its trend (Goodhart et al., 2006; Herrera & Perry, 2001). The difference with credit bubbles is that when stock price bubbles collapse, the stock markets can experience a huge drop and are thereby much more volatile (Alshogeathri, 2011; Goodhart et al., 2006).

This also results in similar operational definitions for stock price bubbles. Alternatives are a deviation from a Hodrick-Prescott filtered trend with 5% for 12 consecutive quarters (Goodhart & Hofmann, 2008) or with at least one standard deviation (Jordà et al., 2015). In addition, the housing bubble definitions used by Shen et al. (2016) can also be used to identify stock price bubbles, as they operationalize similar definitions of bubbles. These definitions are a growth rate above 15% or a deviation from a smooth trend with 1.65 times the standard deviation and a growth rate that exceeds 10%.

Considering these approaches, this study uses two definitions for stock price bubbles similar to Shen et al. (2016). Stock price bubble 1 (SPB1) is a period where the yearly stock price growth rate exceeds 15%. Stock price bubble 2 (SPB2) is a deviation from a Hodrick-Prescott filtered trend with *h* times the standard deviation. Again using a smoothing parameter of 1600. Where Shen et al. (2016) assume *h* to be 1.65, this study assumes *h* to be 1, following Jordà et al. (2016). The motivation behind this is that stock prices can be much more volatile than housing prices. For robustness, different values for *h* and a persisting deviation are also considered.

$$SPB1 = \begin{cases} 1 \ if \ Stock \ price \ growth \ rate > 15\% \\ 0 \ otherwise \end{cases}$$

$$SPB2 = \begin{cases} 1 \ if \ Stock \ Price_{i,t} > \ E(Stock \ Price)_{i,t} + h * \ \sigma_i \\ 0 \ otherwise \end{cases}$$

In the equations above, the Stock price growth rate is the yearly stock price growth rate in percentiles for the respective quarter. Stock price is the real stock price, E(Stock Price) is the expected stock price based on a Hodrick-Prescott filtered trend, h is assumed to be 1 and σ is the standard deviation of the stock price for the respective country.

3.2.3 Models bubble periods

The panel model for bubbles is specified below.

$$\Delta y_{i,t} = (\rho_{0,i} + \rho_1 \Delta y_{i,t-1} + \rho_2 \Delta y_{i,t-2} + \psi_1 \Delta x_{i,t-1} + \psi_2 \Delta x_{i,t-2}) * TB_{i,t} + (\delta_1 \Delta y_{i,t-1} + \delta_2 \Delta y_{i,t-2} + \gamma_1 \Delta x_{i,t-1} + \gamma_2 \Delta x_{i,t-2}) * (1 - TB_{i,t}) + \phi ECM_{i,t-1} + \varepsilon_{i,t}$$

The individual country models are specified as:

$$VEC: \Delta y_t = (\rho_0 + \rho_1 \Delta y_{t-1} \ldots + \rho_p \Delta y_{t-p} + \psi_1 \Delta x_{t-1} \ldots + \psi_p \Delta x_{t-p}) * TB_{i,t} + (\delta_1 \Delta y_{t-1} + \cdots \delta_p \Delta y_{t-p} + \gamma_1 \Delta x_{t-1} \ldots + \gamma_p \Delta x_{t-p}) * (1 - TB_t) + \phi ECM_{t-1} + \varepsilon_t$$

$$VAR: \Delta y_t = (\rho_0 + \rho_1 \Delta y_{t-1} \ldots + \rho_p \Delta y_{t-p} + \psi_1 \Delta x_{t-1} \ldots + \psi_p \Delta x_{t-p}) * TB_{i,t} + (\delta_1 \Delta y_{t-1} \ldots + \delta_p \Delta y_{t-p} + \gamma_1 \Delta x_{t-1} \ldots + \gamma_p \Delta x_{t-p}) * (1 - TB_t) + \varepsilon_t$$

In the equations above, the dummy variable TB = ACB * SPB is one when credit and stock price bubbles occur jointly and zero otherwise. When only credit or stock prices bubbles are considered, TB is replaced by ACB or SPB, respectively. The bubble dummy variables are included in the estimations as an interaction variable with the independent variables, which are lags of ACREDIT and SPINDEX.

The null hypothesis that x does not Granger-cause y during the bubble periods is given by:

$$H_0\ (bubble): \psi_1 = \psi_2 \ldots = \psi_p = 0$$

During non-bubble periods, this hypothesis is given by:

$$H_0\ (non - bubble): \gamma_1 = \gamma_2 \ldots = \gamma_p = 0$$

3.3 Data

The dataset consists of quarterly credit and stock price data from Q2 1980 – Q3 2016 from eight countries. These countries are Malaysia, Japan, Portugal, Belgium, Finland, the Netherlands, France and Germany. These specific countries have been chosen because their data is available over a long time period, and more importantly, these countries are covered by previous literatures that also analyse the relationship between credit and stock prices (Frömmel & Schmidt, 2006; Goodhart et al., 2006; Ibrahim, 2006; Kim & Moreno, 1994; Krainer, 2014; Levieuge, 2017). Data on all credit to the private sector is collected from the bank of international settlements, which documents credit levels in billions of the national currency. For Malaysia and Japan, the currency of this data is converted to Euro using exchange rate data from the World Bank. Data on stock prices is obtained as an index from Morgan Stanley Capital International. This index provides a consistent and seamless global framework with no overlaps or gaps so it can be compared across countries.

4 Results

4.1 Descriptive statistics

Variable	*Observations*	*Mean*	*Std. Dev.*	*Min*	*Max*
SPINDEX	1,099	569.8153	425.8312	16.209	2103.928
ACREDIT	1,128	1526.397	2120.379	7.834	10571.77
ΔSPINDEX	1,091	5.681006	74.71594	-491.354	702.555
ΔACREDIT	1,120	14.21044	144.975	-1202.411	1192.157

TABLE 2 DESCRIPTIVE STATISTICS

Note: 1. SPINDEX refers to MSCI stock price index, ACREDIT refers to all credit to the private sector
2. N = 8 (8 countries) and T = 146 (Q2 1980 – Q3 2016)

Table 2 presents the basic statistics of the whole sample. The means of SPINDEX and ΔSPINDEX are 569.82 and 5.68, respectively. As this concerns an index, the mean of ΔSPINDEX indicates that on average, the stock price index increases by 5.68 points each quarter. The means of ACREDIT and ΔACREDIT are 1526.40 and 14.21, respectively. For example, the mean ΔACREDIT of 14.21 indicates that on average credit increases with €14.21 billion each quarter. The number of observations of SPINDEX is lower than the number of observations of ACREDIT, because for Malaysia, Finland and Portugal the stock price indexes are only available from 1988, 1982 and 1988 respectively.

Table 14 in appendix 1 presents the basic statistics per country. The mean of ΔACREDIT is the largest in Japan at 44.33 and the smallest in Portugal at 2.35. The mean of ΔSPINDEX is largest in France at 10.00 and smallest in Portugal at -0.24, unexpectedly indicating a decrease in credit over the years. The largest change of -1202.411 in ACREDIT is in Japan. The largest change in the stock price index is 702.55 in Finland. The standard deviation of ΔACREDIT ranges from 3.24 in Finland to 400.97 in Japan. The standard deviation of ΔSPINDEX ranges from 15.50 in Portugal to 108.84 in Finland.

Figure 2 and Figure 3 plot the stock price indexes for each country, were the black shades indicate stock price bubbles. In Figure 2, stock price bubbles are defined as a high growth rate (SPB1), and in Figure 3 they are defined as a strong deviation from their trend (SPB2). The figures show that both definitions identify at least the well-known bubbles, like the bubbles in

2000 and 2007/2008. However, SPB1 also indicates many smaller bubbles. For robustness, other definitions of stock price bubbles were also considered, but these did not identify the well-known bubbles better.

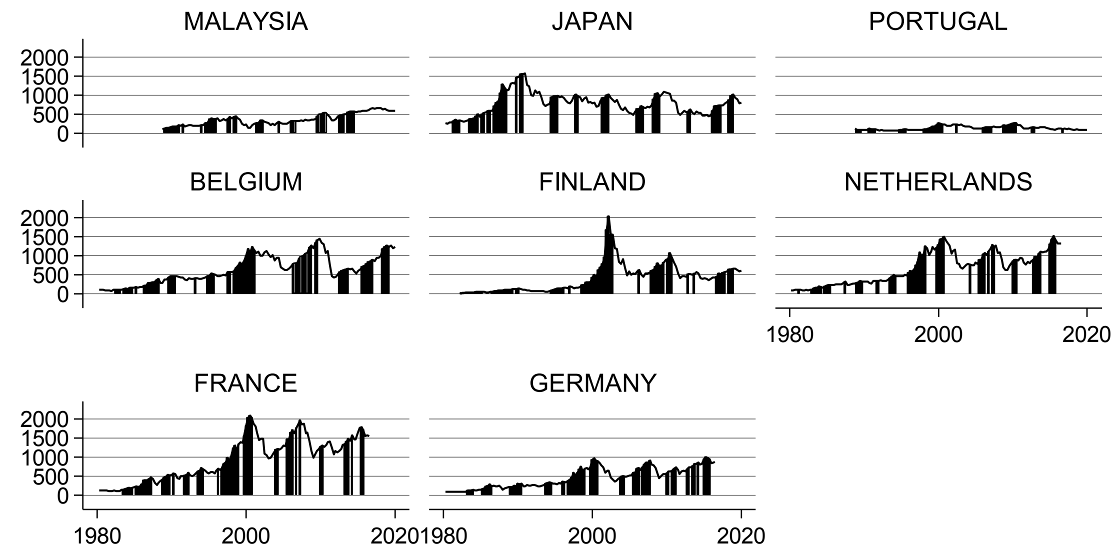


FIGURE 2 STOCK PRICE UNDER STOCK PRICE BOOM (SPB1)

Notes: The line indicates the stock price index. The black shades indicate stock price bubbles according to definition 1.

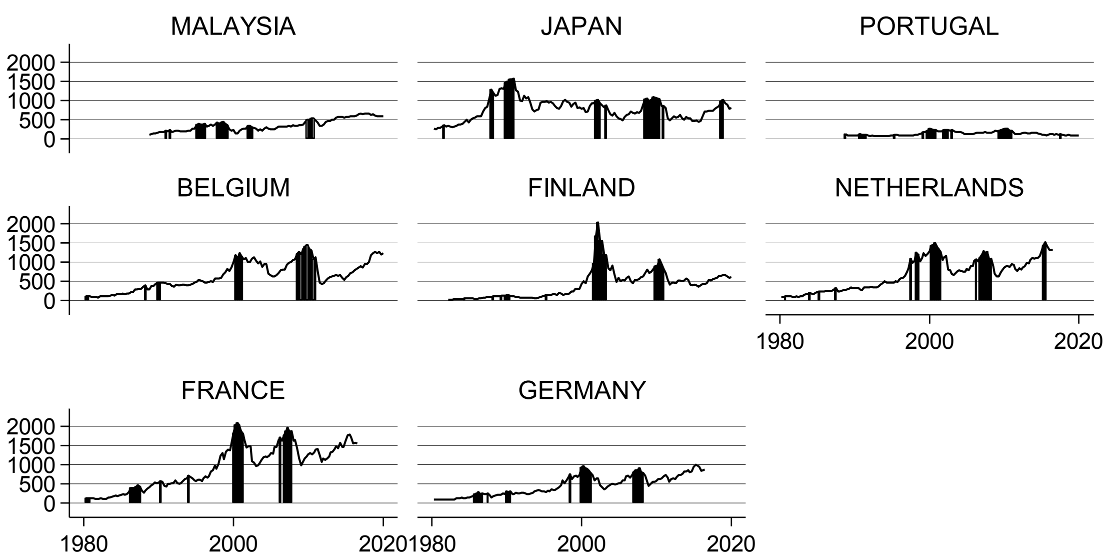


FIGURE 3 STOCK PRICE UNDER STOCK PRICE BOOM (SPB2)

Notes: The line indicates the stock price index. The black shades indicate stock price bubbles according to definition 2.

Figure 4 and Figure 5 plot credit levels for each country, in which the black shades indicate bubbles based on high growth rates (ACB1) and a strong deviation from the trend (ACB2), respectively. The figures show that no ACB1 observations are identified in Germany. In addition, credit levels only fluctuate in Japan, while being more stable in the other countries.

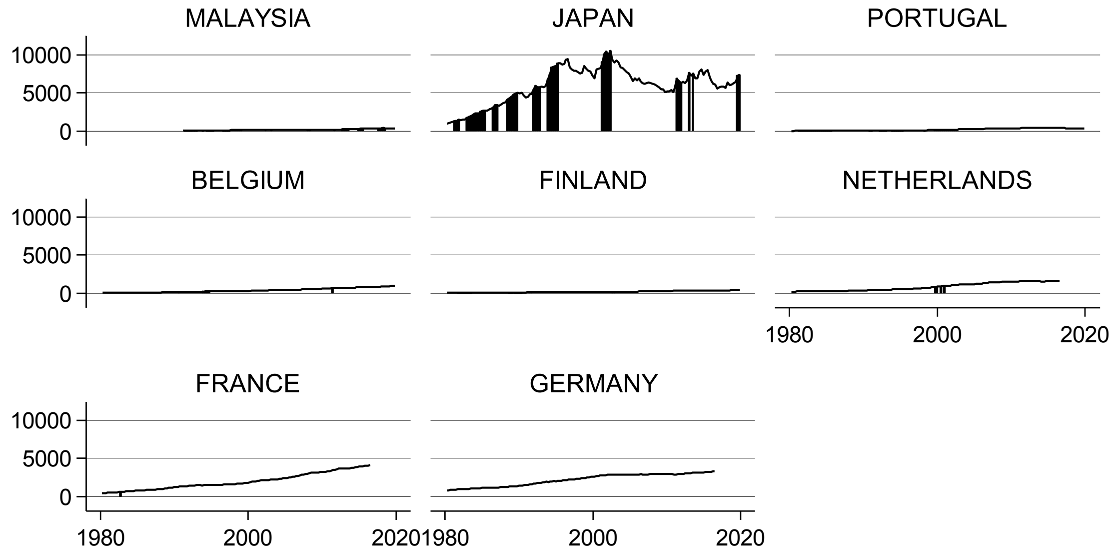


FIGURE 4 CREDIT UNDER CREDIT BOOM (ACB1)

Notes: The line indicates the credit level. The black shades indicate credit bubbles according to definition 1.

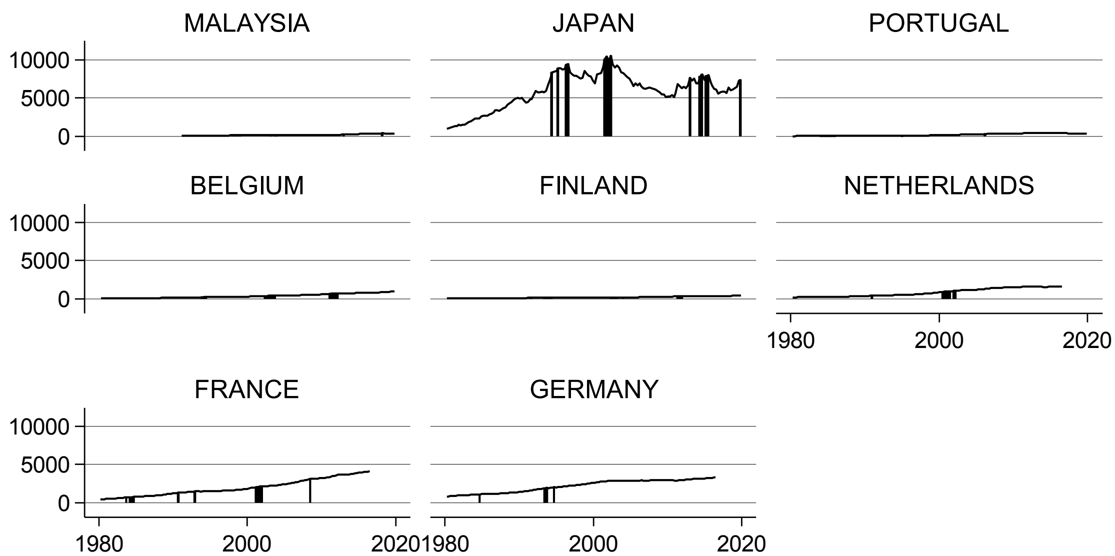


FIGURE 5 CREDIT UNDER CREDIT BOOM (ACB2)

Notes: The line indicates the credit level. The black shades indicate credit bubbles according to definition 2.

Table 3 presents the frequencies of stock price bubbles and credit bubbles by each country. This table shows that the bubble definitions based on a high growth rate identify more bubbles than the definitions based on a strong deviation from the trend. Table 3 also presents the frequencies of twin bubbles and shows that these do not occur often. In fact, there are no TB1 observations in France and Germany. In addition, there are no TB2 observations in Portugal, Belgium and Germany. Table 15 in appendix 1 presents the frequencies of bubbles by year. This table shows that SPB1 and SPB2 occur most around 1989, 2000 and 2007 and ACB1 and ACB2 occur most around 1984, 1993 and 2000. TB1 shows small peaks in 1993 and 2000, while TB2 clearly occurs most around 2000.

	SPB1	*SPB2*	*ACB1*	*ACB2*	*TB1*	*TB2*
MALAYSIA	40	20	38	10	13	5
JAPAN	51	23	44	14	23	3
PORTUGAL	37	24	42	10	11	0
BELGIUM	66	19	6	14	1	0
FINLAND	69	19	17	15	10	4
NETHERLANDS	57	23	4	8	3	5
FRANCE	60	23	1	11	0	1
GERMANY	64	22	0	4	0	0
Total	444	173	152	86	61	18

TABLE 3 NUMBER OF QUARTALS WITH BUBBLES BY COUNTRY

Notes: 1. SPB1: stock price growth rate exceeds 15%. SPB2: deviation of 1 standard deviation from a smooth trend.
2. ACB1: credit growth rate exceeds 15%. ACB2: deviation of 1.5 standard deviation from a smooth trend.
3. TB1: twin boom 1, which denotes that stock price boom and credit boom occur simultaneously. TB1 = SPB1 * ACB1, TB2 = SPB2 * ACB2.

4.2 Panel analysis

4.2.1 Panel unit root and cointegration

Table 4 reports the results of the panel unit root test by Im, Pesaran and Shin. This panel unit root test allows for cross-section unit root processes. The statistics for SPINDEX and ACREDIT are -1.145 and 3.687 and their corresponding P-values are 0.126 and 1.000, respectively. Hence, the null hypothesis of individual unit root processes cannot be rejected, suggesting that SPINDEX and ACREDIT are non-stationary. The statistics and corresponding P-values for ΔSPINDEX and ΔACREDIT are -25.161 and -16.547, and 0.000 and 0.000, respectively. Indicating that the null hypothesis can be rejected. Hence, SPINDEX and ACREDIT are I(1).

	SPINDEX	*ACREDIT*	*ΔSPINDEX*	*ΔACREDIT*
Im, Pesaran and Shin W-stat	-1.145	3.687	-25.161	-16.547
P value	0.126	1.000	0.000	0.000
t-statistics in parentheses				

TABLE 4 PANEL UNIT ROOT TESTS

Note: 1. Im, Paseran and Shin's panel unit root test
2. H0: individual unit root process
3. N: 8, T=146 (Q2 1980 – Q3 2016)

Table 5 presents the panel cointegration test results. This study uses the residual-based panel cointegration test by Pedroni (1999), to assess whether a cointegration relationship exists between the variables ACREDIT and SPINDEX. The panel-*p,* panel-*t,* and panel-*ADF* statistics are all significant. Hence, the null hypothesis of no cointegration can be rejected. Therefore, the panel error-correction model can be used.

Test Stats.	*Panel*	*Group*
v	2.531	.
rho	-1.7***	.6467
t	1.411***	.9251
adf	2.457***	2.483

TABLE 5 PANEL COINTEGRATION TEST RESULTS

Note: 1. H(0): No cointegration
2. Number of panel units: 8. Number of repressors: 1.
3. Observations: 1090, average observation per unit: 136.
4. Data has not been time-demeaned. A time trend has been included.
5. The critical value is based on Pedroni (1999). * P<0.10, ** P< 0,05, *** P<0,01.

4.2.2 Panel causality

Table 20 in Appendix 2 presents the coefficients from a regression, panel regression and GMM estimation. This table suggests that the GMM estimator provides valid results, because the coefficients are close to those of the normal and panel regressions (Roodman, 2006). When stock prices and credit are used as the dependent variables, they are referred to as stock price and credit regressions respectively.

Table 6 shows the result of the GMM and DFE estimations for the whole sample. These results indicate that the first lags of the dependent variables are all positively related to the dependent variable. This suggests that consecutive quarters usually follow the same trend, which makes sense. The F statistic of the whole model is significant for both regressions with both estimators, which suggests that the models help to explain the dependent variables.

	GMM		*DFE*	
	ΔSPINDEX	*ΔACREDIT*	*ΔSPINDEX*	*ΔACREDIT*
LD.SPINDEX	0.135*	-0.014	0.215***	-0.027
L2D.SPINDEX	-0.072	-0.023	0.052*	-0.029**
LD.ACREDIT	-0.056*	0.117***	0.006**	0.113***
L2D.ACREDIT	-0.049**	-0.039**	0.009***	-0.040***
qdate	-2.050	-0.113	0.293**	0.057
ECM	0.073	-0.018	-0.050***	-0.029***
_Cons	349.144	29.221	-10.146	25.686**
F value	0.001	0.000	0.000	0.000
F SP>AC		0.435		0.015
F AC>SP	0.026		0.000	

** p<0.05, **p<0.01,*** p<0.001*

TABLE 6 PANEL ERROR CORRECTION MODELS BETWEEN STOCK PRICE AND CREDIT

1. Arellano and Bond's GMM estimator (GMM) and cross-country dynamic fixed effects (DFE)
2. N: 1066, Panels: 8.
3. F value is the joint test examining the null hypothesis that the coefficients do not Granger cause y.
4. F SP>AC (F AC>SP) is the tests examining the null hypothesis that the coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX)
5. ECM is an error correction term.

Figure 6 presents a graphical overview of the short and long run relationships between the variables in the whole sample suggested by both estimators. The F statistic indicating that credit affects stock prices is significant with both estimators. This suggests that credit has a short-run effect on stock prices. However, the coefficients of ACREDIT in the stock price regression are negative with GMM and positive with DFE. This is rather strange, as both methods estimate a similar model. Yet, the estimators differ slightly as mentioned in section 3.1.1. Moreover, the absolute difference between the coefficients is relatively small. Unfortunately, one cannot determine the effect of this relationship due to these contrasting coefficients. Only for the DFE estimator, the F statistic indicates that stock prices affect credit. This can be explained, as the coefficients of SPINDEX in the credit regression are negative for both estimators, but only significant with the DFE estimator. Therefore, the results hint at a confirmation of the hypothesis that stock prices affect credit in the short-run, but there remains some uncertainty. The coefficients of ECM are only significant with DFE, but they do indicate that the variables move to a long-run equilibrium.

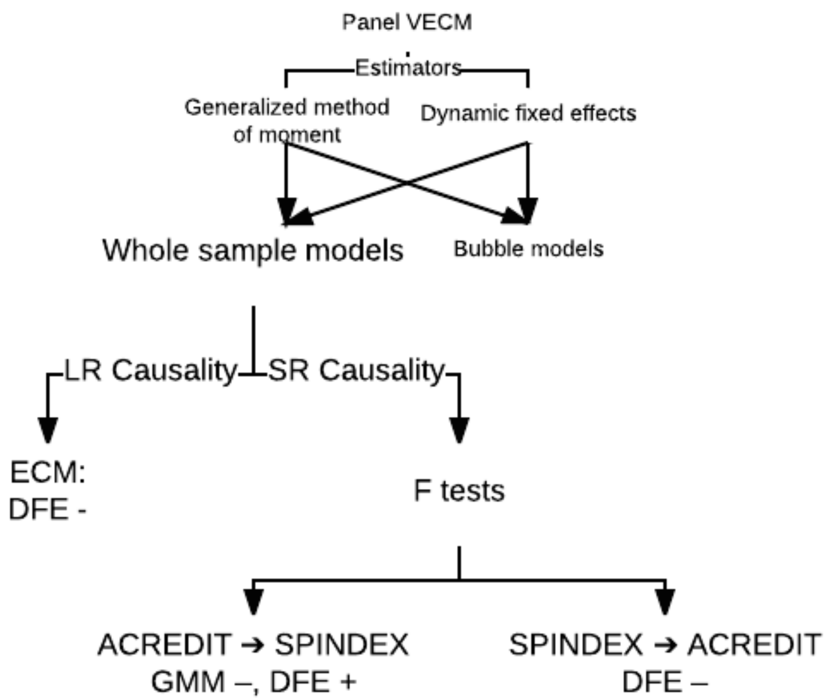


FIGURE 6 GRAPHICAL DISPLAY CAUSALITY RESULTS OF PANEL MODELS

Note: 1. Long-run (LR) causality based on the coefficients of ECM
2. Short-run (SR) causality is based on the F tests
3. Positive or negative sign behind the estimator indicates the direction of the relationship found.

4.2.3 Panel causality bubble periods

Table 7 presents an example of the output from the GMM estimator during bubbles. The interpretation of the output from the DFE estimator is similar to that of the GMM estimator, except that this does not include AR tests and Sargan or Hansen tests. The variables multiplied by SPB proxy the interaction terms in bubble periods and by nonSPB proxy non-bubble periods. The F-value indicates that the model itself is significant. The coefficients of the first lag of SPINDEX in bubbles in the stock price regression are positive, suggesting a normal trend. However, the coefficients of credit in bubbles in the credit regression are negative. This suggests that in stock price bubbles, a positive change in credit is followed by a negative change in the next quarter and vice versa. However, the second lag of credit in the credit regression is positive. This can be explained by a higher volatility in bubble periods (Cochrane, 2002). In addition, the bubble coefficients of ACREDIT in the credit regression are significantly larger than the non-bubble coefficients, which also suggests that credit is more volatile in stock price bubbles.

In regard of causality, the F statistics in Table 7 suggest that the null of no causality can only be rejected at 10% confidence for credit to stock prices in SPB1. Thereby providing no convincing evidence for short-run causality between the variables. The coefficients of ECM indicate a long-run relationship, as they are negative and significant. This is in contrast to the GMM estimator without bubbles, which did not indicate a long-run relationship.

The test statistics make suggestions about the validity of the model. The AR test statistics indicate that the null of no autocorrelation cannot be rejected for the second lags. Sometimes, the AR test is omitted, like in Table 7, because the bubble measure excludes samples so that there are too little third lags in difference. One can include the level values, but this provides more worrisome results than the omitted AR tests. The null hypothesis of the Sargan test statistic is that the instruments are valid. However, in all analyses, the number of instruments is larger than the number of groups. As a result, the Sargan and Hansen tests are unreliable (Samargandi et al., 2015).

The results from all panel analyses with bubbles are presented in Table 21 to Table 25 in Appendix 2. The coefficients of ECM indicate in almost all cases long-run causality between both variables, which is in contrast to the whole sample analysis using the GMM estimator. In addition, the coefficients of the first lag of the non-bubble dependent variables are always positive, indicating a normal trend. In contrast, the coefficients of the first lags of the dependent variables in bubbles are positive in only 12 out of 24 cases. In six of the remaining cases, the second lag of the dependent variable is positive. This can still indicate growth, while the negative coefficient of the first lag can be explained by higher volatility in bubbles (Cochrane, 2002). However, in six cases, not a single coefficient of the lags is positive in bubble periods. This especially occurs in twin bubbles. A higher volatility in bubble periods can help to explain this, but it is more likely that the bubble observations include most of the highest values in the sample. This is good, since that is the objective when identifying bubbles. However, especially for twin bubbles, the sample includes most of the exceptionally high observations, as shown by the high means of the variables in bubble observations in comparison to non-bubble observations (Table 16 - Table 19, Appendix 1). Therefore, the proceeding observations are likely to be lower, explaining the negative coefficients.

	SPB1		*SPB2*	
	ΔSPINDEX	*ΔACREDIT*	*ΔSPINDEX*	*ΔACREDIT*
*LD.SPINDEX*SPB*	0.240***	-0.175	0.132*	-0.139
*L2D.SPINDEX*SPB*	0.036	-0.216	0.183*	-0.189
*LD.ACREDIT*SPB*	-0.016	-0.076	-0.002	-1.330***
*L2D.ACREDIT*SPB*	0.124	0.658***	0.060	1.439*
*LD.SPINDEX*nonSPB*	0.190***	0.070	0.258***	-0.005
*L2D.SPINDEX*nonSPB*	0.036	-0.002	0.008	-0.034
*LD.ACREDIT*nonSPB*	-0.000	0.101*	0.008	0.269***
*L2D.ACREDIT*nonSPB*	-0.039	-0.296***	-0.003	-0.306
ECM	-0.034*	-0.026*	-0.047**	-0.027*
qdate	0.097	0.156	0.128	0.048
_Cons	-12.263	-7.361	-16.594	7.696
Test statistics:				
AR(1): Pr > z=	0.000	0.000	0.000	.
AR(2): Pr > z=	0.204	0.363	0.138	.
Sargan: Prob > chi2=	0.000	0.469	0.000	0.751
Hansen: Prob > chi2=				
Sample:				
Observations	1066	1066	1066	1066
Groups	8	8	8	8
Instruments	21	12	21	12
F tests:				
F value	0.000	0.000	0.000	0.000
*SP*SPB>AC*		0.116		0.389
*SP*nonSPB>AC*		0.754		0.943
*AC*SPB>SP*	0.099		0.812	
*AC*nonSPB>SP*	0.372		0.913	

** p<0.05, ** p<0.01, *** p<0.001*

TABLE 7 PANEL ERROR CORRECTION MODEL DURING STOCK PRICE BOOMS (GMM)

1. SPB1: stock price growth rate exceeds 15%. SPB2: deviation of 1 standard deviation from a smooth trend.
2. Arellano and Bond's GMM estimator
3. F value is the joint test examining the null hypothesis that the coefficients do not Granger cause y.
4. F SP>AC (F AC>SP) is the tests examining the null hypothesis that the coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) by bubble and non-bubble observations.
5. ECM is an error correction term.

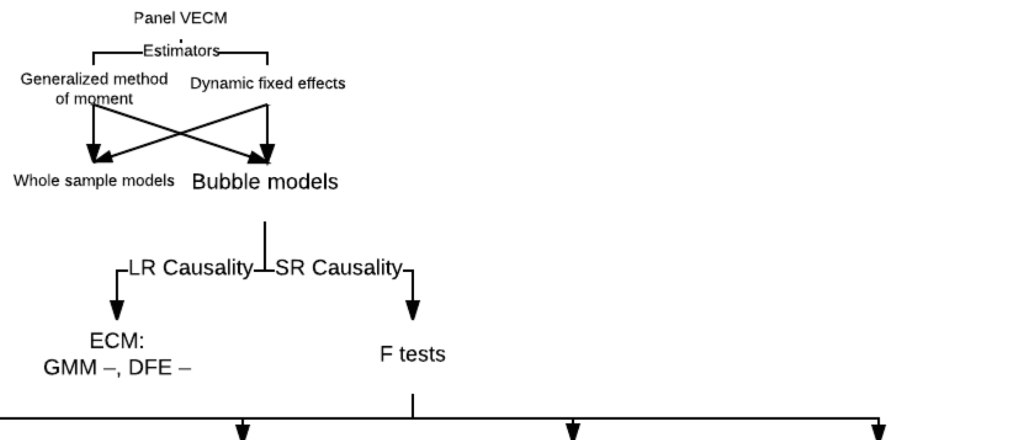
Table 8 presents an overview of the short-run relationships that are supported by the F statistics. Figure 7 presents a graphical overview of these relationships and indicates the direction of this relationship. Both estimators suggest causality from credit to stock prices in SPB1, credit bubbles, non-credit bubbles and twin bubbles. In addition, the coefficients of credit in all bubbles are merely positive (Table 21 - Table 25, Appendix 2). For SPB2, non-stock price bubbles and non-twin bubbles, only the DFE estimator indicates causality from credit to stock prices. In these analyses, the coefficients of credit are also positive in bubble periods. In all non-bubble analysis, the coefficients of credit in the stock price regression are negative or very close to zero.

There is less evidence for a short-run relationship from stock prices to credit. Only in ACB1 and nonACB1, both estimators indicate that stock prices affect credit. With both estimators, the coefficients of SPINDEX in the credit regression with ACB1 are positive for bubble periods and negative for non-bubble periods. The coefficients of ACREDIT in this regression are similar to the other analyses, supporting the validity of this model. However, it is strange that this causality is only found with ACB1 and not ACB2. Comparing the coefficients under both bubble definitions, it is noticeable that the coefficients with ACB2 are somewhat smaller, but their directions match. This would explain why the F tests of ACB2 fail to reject the null hypothesis that the coefficients of SPINDEX are 0. The DFE estimator also suggests causality from stock prices to credit in SPB1, non-SPB2, non-ACB2, twin bubbles and non-twin bubbles. Again, the coefficients in bubble periods are merely positive while the coefficients in non-bubble periods are more negative.

	GMM		**DFE**	
Causality	**SP>AC**	**AC>SP**	**SP>AC**	**AC>SP**
Entire sample		X*	X*	X*
SPB1		X**	X**	X*
SPB2				X*
nonSPB1				X*
nonSPB2			X*	X*
ACB1	X*	X**	X**	X*
ACB2		X*		X*
nonACB1	X*	X**	X*	X*
nonACB2		X*	X*	X*
TB1		X*	X*	X*
TB2		X**	X*	X*
nonTB1			X**	X*
nonTB2			X*	X*

TABLE 8 OVERVIEW RELATIONSHIPS FROM PANEL ERROR CORRECTION MODELS GMM AND DFE

Notes: 1. Table displays causality according to Wald F-tests. F-values of the models are excluded, as they all indicate causality.
2. * P<0.05, ** P>0.10.



	ACREDIT*B ➔ SPINDEX	ACREDIT*nonB ➔ SPINDEX	SPINDEX*B ➔ ACREDIT	SPINDEX*nonB ➔ ACREDIT
SPB	GMM +, DFE +*	DFE –		
ACB	GMM +, DFE +	GMM –, DFE –	GMM +, DFE +*	GMM –, DFE –*
TB	GMM +, DFE +	DFE –	DFE +	DFE –

FIGURE 7 GRAPHICAL DISPLAY CAUSALITY RESULTS OF PANEL BUBBLE MODELS

Note: 1. Long-run (LR) causality is based on coefficients ECM
2. Short-run (SR) causality is based on the F tests
3. Positive or negative sign indicates the direction of the relationship found.
4. * Indicates that the finding is not robust to the bubble definitions.
5. B indicates the bubble period and nonB indicates the non-bubble period.

4.3 Country individual analysis

4.3.1 Unit root tests & cointegration tests

Table 26 in Appendix 3 presents the Augmented Dickey-Fuller tests for unit root. The number of lags is based on sequential lag reduction tests starting at 12 lags and adjusted downwards if the Z(t) statistic is larger then -1.000 (Goodhart et al., 2004). The probability that the null hypothesis of individual unit root can be rejected for SPINDEX ranges from 0.084 in Belgium to 0.740 in Malaysia. For ACREDIT, this ranges from 0.480 in Portugal to 0.936 in Malaysia. Thereby suggesting that the null hypothesis cannot be rejected for SPINDEX and ACREDIT with 95% confidence. For ΔSPINDEX and ΔACREDIT the probability that the null hypothesis can be rejected is at maximum 0.031, indicating that ΔSPINDEX and ΔACREDIT are I(1) for all countries.

Table 27 - Table 34 in Appendix 3 present the results of the Johansen tests for cointegration for each individual country. The number of lags is determined based on AIC. The results indicate that for Malaysia, Belgium, Finland, France and Germany, the variables are cointegrated in rank

zero. Hence, VAR models are used for these countries. For Japan, Portugal and the Netherlands, the results indicate cointegration in rank 1 or higher. Hence, VEC models are used for these countries.

4.3.2 Causality individual countries

Table 9 and Table 10 present the results from the whole country VAR and VEC models, respectively. In all countries, there is a positive effect of the first lag of the dependent variable, in line with the whole sample analysis. In later lags, a correction can occur. One exception is credit in Germany, where the coefficients of all six lags are positive indicating steady growth. In Finland and France, the coefficients of the lags of the variables are also all in the same direction. However, this can be a consequence of the maximum lag length being just two for these countries.

Figure 8 presents a graphical overview of the results from the Granger-causality tests. These test indicate causality from stock prices to credit only in Malaysia, Belgium, Portugal and the Netherlands. The coefficients indicate that this relationship is negative for Portugal and the Netherlands and positive for Malaysia, but for Belgium one cannot determine a direction. Causality from credit to stock prices is suggested only for Finland, Germany and the Netherlands, being a negative relationship in Finland and Germany and a positive relationship in the Netherlands. Thus, there is only evidence for short-run two-way causality in the Netherlands. In addition, the coefficients of ECM indicate that in the Netherlands, there also is a two-way relationship in the long run. In Japan and Portugal, the coefficients of ECM only indicate a long-run relationship from stock prices to credit. In sum, the Granger tests, F tests and coefficients of ECM indicate that the direction of causality can differ across countries.

For a robustness test, impulse response functions are used. These results are presented in Appendix 3. Figure 10 and Figure 11 display the IRFs for the VAR models and Figure 12 and Figure 13 for the VEC models. These results support the previous findings that stock prices affect credit in Malaysia and Belgium, but fail to do this in Portugal and the Netherlands. Only for Japan, the IRF results indicate that stock prices affect credit after 10 periods. This is in line with the long-run relationship found by the VEC models, but these also suggest a long-run relationship in Portugal and the Netherlands. Furthermore, the IRF results indicate that only in Finland, Germany and the Netherlands, credit has a significant impact on stock prices. This is in line with the respective VAR and VEC results. In conclusion, the IRF results support the VAR findings, but fail to do this for some of the VEC findings.

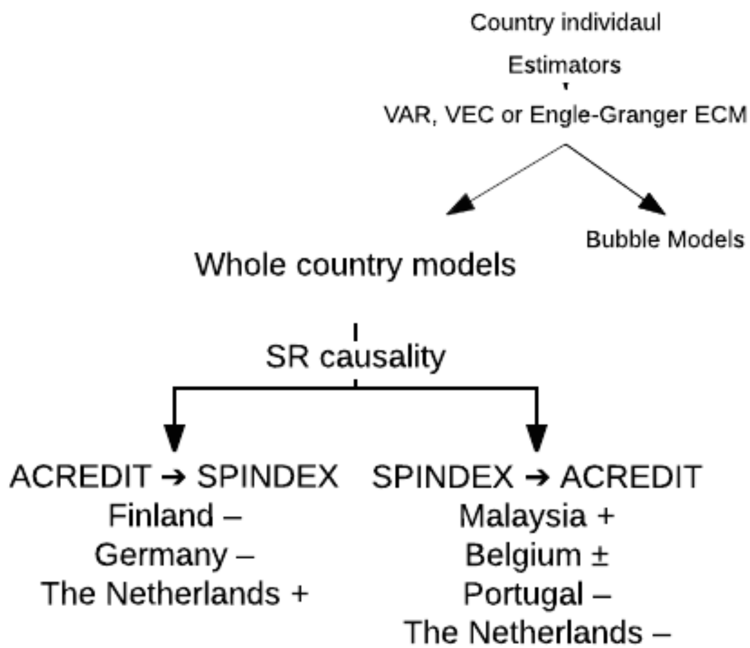


Figure 8 Graphical overview relationships whole country analyses

Note: 1. Short-run (SR) causality is based on the F tests and Granger causality tests
2. Positive or negative sign indicates the direction of the relationship found.

	Malaysia	*Belgium*	*Finland*	*France*	*Germany*
ΔSPINDEX					
L.ΔSPINDEX	0.135	0.096	0.163	0.240**	0.206*
L2.ΔSPINDEX	0.027	0.110	0.018	0.033	-0.007
L3.ΔSPINDEX	0.158	0.165			0.040
L4.ΔSPINDEX	-0.257**	-0.058			0.005
L5.ΔSPINDEX	-0.135	0.004			-0.067
L6.ΔSPINDEX	-0.127	-0.000			
L7.ΔSPINDEX		-0.119			
L8.ΔSPINDEX		-0.098			
L.ΔACREDIT	0.196	-1.880	-5.491	-0.341	-0.289
L2.ΔACREDIT	0.122	-0.367	-4.367	-0.617	0.291
L3.ΔACREDIT	-0.126	0.297			0.254
L4.ΔACREDIT	0.449	1.393			-0.788***
L5.ΔACREDIT	-0.455	1.791			0.435
L6.ΔACREDIT	-0.588	-2.250			
L7.ΔACREDIT		-2.043			
L8.ΔACREDIT		-0.070			
_Cons	6.644	25.288*	28.642*	31.325*	6.364
ΔACREDIT					
L.ΔSPINDEX	-0.021	-0.011	0.002	0.002	0.042
L2.ΔSPINDEX	0.071*	0.006	0.002	0.010	-0.014
L3.ΔSPINDEX	-0.004	-0.000			0.009
L4.ΔSPINDEX	0.067*	0.013			0.034
L5.ΔSPINDEX	-0.078**	0.007			0.039
L6.ΔSPINDEX	0.034	0.000			
L7.ΔSPINDEX		0.018*			
L8.ΔSPINDEX		0.007			
L.ΔACREDIT	0.178	0.126	0.372***	0.400***	0.068
L2.ΔACREDIT	-0.272**	0.159	0.005	0.281***	0.126
L3.ΔACREDIT	0.130	0.084			0.021
L4.ΔACREDIT	-0.191	0.412***			0.442***
L5.ΔACREDIT	0.035	-0.065			0.038
L6.ΔACREDIT	0.047	-0.163			
L7.ΔACREDIT		-0.077			
L8.ΔACREDIT		0.074			
_Cons	3.055*	2.515**	1.554***	8.066***	4.754
Granger Tests:					
SP>AC	0.021	0.029	0.371	0.727	0.265
AC>SP	0.210	0.192	0.011	0.125	0.009

** p<0.05, ** p<0.01, *** p<0.001*

TABLE 9 INDIVIDUAL VAR MODELS

1. N: 146
2. The granger test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX)
3. Lags are selected using the AIC selection criterion.

	Japan		*Portugal*		*Netherlands*	
	ΔSPINDEX	*ΔACREDIT*	*ΔSPINDEX*	*ΔACREDIT*	*ΔSPINDEX*	*ΔACREDIT*
ECM	-0.021	-0.037**	-0.078	-0.009***	-0.092*	-0.008**
LD.SPINDEX	0.245**	-0.136	0.278**	-0.047	0.108	-0.006
L2D.SPINDEX	-0.045	-0.007	0.106	-0.032	0.056	-0.041***
L3D.SPINDEX	0.099	-0.695	0.084	0.000	0.323***	0.017
L4D.SPINDEX	-0.048	-0.723			0.012	-0.004
LD.ACREDIT	0.006	0.105	0.645	0.040	2.549***	0.239**
L2D.ACREDIT	0.000	-0.060	0.072	0.220*	-0.584	0.080
L3D.ACREDIT	0.037*	0.211*	-0.292	-0.069	-0.335	-0.148
L4D.ACREDIT	-0.016	-0.021			-0.268	0.174*
_Cons	4.656	0.376	0.692	1.236**	0.841	5.316***
F Tests:						
SP>AC		0.134		0.097		0.011
AC>SP	0.310		0.414		0.001	

** p<0.05, ** p<0.01, *** p<0.001*

TABLE 10 INDIVIDUAL VEC MODELS

1. N: 146
2. The table contains coefficients from two VEC models, one with SPINDEX and one with ACREDIT as dependent variable, but only shows the coefficients on the dependent variable.
3. The F test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX)
4. Lags are selected using the AIC selection criterion.

4.3.3 Causality bubbles individual countries

Table 11 and Table 12 present examples of the output of respectively VAR and EG-ECM models during bubbles and non-bubbles. In both models, the non-bubble lags of the dependent variable are omitted because of collinearity problems with the normal lags of the dependent variable. Similar to the non-bubble analysis, the coefficients of the first lag of the dependent variables are always positive, but the coefficients of their bubble equivalent can also be negative. Just as in the panel bubble analyses, this can be explained by prices being more volatile in periods of bubbles (Cochrane, 2002). The coefficients of ECM in Table 12 indicate that there is an explosive long-run relationship from credit to stock prices in Japan.

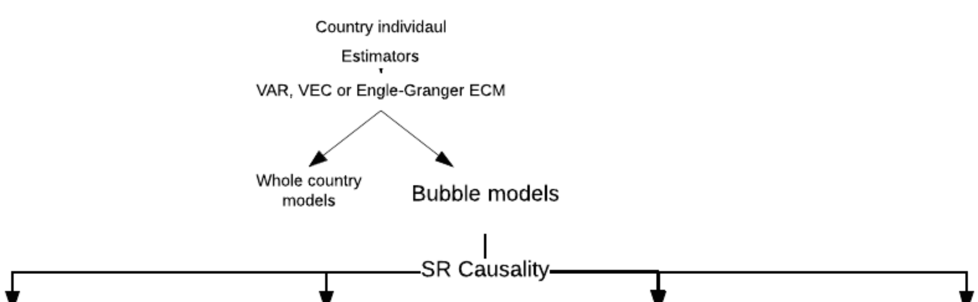
In Malaysia, the F statistics suggest causality from stock prices to credit in bubbles for both credit bubble definitions. In addition, these statistics suggest causality from stock prices to credit in non-ACB2 with 10% confidence. Both are in line with the non-bubble analysis for Malaysia. For Japan, the F statistics fail to reject the null hypothesis that the coefficients are zero, indicating that there is no causality between the variables in stock price bubbles. This is plausible, since the non-bubble analysis in Japan neither indicate causality between the two variables.

The results of the analyses of all countries are presented in Appendix 3, from Table 35 to Table 53. These tables show that the coefficients of the first lag of the dependent variables are positive in all but two cases. In these two cases, the second lag of the dependent variable is positive, which is still somewhat normal. In Portugal and the Netherlands, the coefficients of ECM indicate a two-way long-run relationship, while in Japan they do not. There is no unambiguous trend among the first lags of the dependent variables in bubbles. These can be positive or negative, differing between countries and within countries between the bubble definitions.

Table 13 presents an overview of the relationships from the individual country analysis and Figure 9 presents a graphical overview of these relationships and their directions. These show that only in the Netherlands, there is strong evidence for a two-way relationship between credit and stock prices. In fact, causality from credit to stock prices is robust for all but the twin bubble measures in the Netherlands. Moreover, the coefficients of the first lag of credit are positive in stock price bubbles, ACB2 and TB2, but not in ACB1. Remarkably, all first lags of credit in non-bubbles are also positive. Causality from stock prices to credit is found for all first bubble definitions and only for non-ACB2 and non-TB2. For SPB1 and ACB1, the coefficients of later lags of SPINDEX are significant and positive in the credit regression, but not for TB1. This could be explained as twin bubbles include most of the highest observations of stock prices (Table 17 & Table 19, Appendix 1). In contrast to the analysis without bubbles, the non-bubble coefficients are negative for the first lags and positive for later lags.

In Belgium, Finland and Germany, there is strong evidence that credit affects stock prices in periods of stock price bubbles. All coefficients of the first lags of credit are negative in these relationships. This is confirmed for some other bubble or non-bubble analysis, but these are not robust for the bubble definitions. In addition, the results suggest a negative relationship from credit to stock prices in twin bubbles in Malaysia. For Germany and Finland the whole sample analyses also suggest a relationship from credit to stock prices, but for Belgium and Malaysia the whole sample analyses only indicate causality from stock prices to credit. In contrast, the bubble analyses for Belgium provide poor evidence for this relationship. Thereby indicating that the relationship between the variables can be sensitive to bubble periods.

Only in Malaysia, the bubble analyses suggest a positive one-way relationship from stock prices to credit in credit bubbles, non-stock price bubbles and non-twin bubbles. This is in line with the whole sample analysis of Malaysia that also suggests this relationship. For Portugal, the whole sample analysis did too, but the bubble analyses indicate that there is no causality between the variables in bubbles or non-bubbles. Other countries for which the bubble analyses do not indicate causality between the variables are France and Japan.



	ACREDIT*B ➔ SPINDEX	ACREDIT*nonB ➔ SPINDEX	SPINDEX*B ➔ ACREDIT	SPINDEX*nonB ➔ ACREDIT
SPB	NL +, BE –, FI –, DE –	NL+	NL +	NL –, MY +
ACB	NL +	NL +	NL +, MY +	NL –
TB	MY –	NL +, FI –		NL –, MY +

FIGURE 9 GRAPHICAL OVERVIEW CAUSAL RELATIONSHIPS COUNTRY BUBBLE ANALYSES

Note: 1. Short-run (SR) causality is based on the F tests and Granger causality tests
2. Positive or negative sign indicates the direction of the relationship found.
3. B indicates the respective bubble periods and nonB indicate the respective non-bubble periods.

Malaysia	ACB1		ACB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
L.Y	0.137	0.226	0.101	0.306**
L2.Y	-0.063	-0.219	-0.058	-0.048
L3.Y	0.080	0.283	0.182	0.157
L4.Y	-0.132	0.044	-0.298**	-0.187
L5.Y	-0.212	0.009	-0.241*	0.086
L6.Y	-0.194	0.186	-0.179	0.281*
L.SPINDEX*ACB	-0.031	0.031	-0.008	0.189*
L2.SPINDEX*ACB	0.360	0.096	0.721*	0.256**
L3.SPINDEX*ACB	0.288	-0.026	0.125	-0.136
L4.SPINDEX*ACB	-0.284	0.110*	0.285	0.091
L5.SPINDEX*ACB	0.067	-0.106*	0.772*	0.056
L6.SPINDEX*ACB	0.051	0.042	0.507	0.153
L.ACREDIT*ACB	-0.016	-0.079	0.223	-0.617**
L2.ACREDIT*ACB	-0.305	-0.118	-0.153	-0.431*
L3.ACREDIT*ACB	-0.185	-0.203	-1.034	0.146
L4.ACREDIT*ACB	0.636	-0.517**	0.558	-0.138
L5.ACREDIT*ACB	-0.321	0.195	-0.742	-0.239
L6.ACREDIT*ACB	-0.734	-0.144	-0.881	-0.423*
L.ACREDIT*nonACB	0.251		-0.420	
L2.ACREDIT*nonACB	0.390		0.321	
L3.ACREDIT*nonACB	0.384		0.096	
L4.ACREDIT*nonACB	0.689		0.293	
L5.ACREDIT*nonACB	-0.873		-0.491	
L6.ACREDIT*nonACB	-0.308		-0.231	
L.SPINDEX*nonACB		-0.057		-0.045
L2.SPINDEX*nonACB		0.064		0.053
L3.SPINDEX*nonACB		0.021		0.001
L4.SPINDEX*nonACB		0.037		0.030
L5.SPINDEX*nonACB		-0.074*		-0.086**
L6.SPINDEX*nonACB		0.020		0.038
Constant	7.005	3.235**	11.652**	3.434**
Granger tests:				
SP*ACB>AC		0.034		0.001
SP*nonACB>AC		0.128		0.052
AC*ACB>SP	0.504		0.246	
AC*nonACB>SP	0.438		0.753	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 11 VAR MALAYSIA: CREDIT BUBBLES

1. N: 99
2. Y corresponds to the dependent variable
3. The Granger test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations.
4. Lags are selected using the AIC selection criterion.
5. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
6. Acb1: credit growth rate exceeds 15%. Acb2: deviation of 1,5 standard deviation from a smooth trend.

Japan	SPB1		SPB2	
	ΔSPINDE	ΔACREDIT	ΔSPINDEX	ΔACREDIT
ECM	0.003	-0.003	0.091**	-0.006
LD.Y	0.251*	0.079	0.198	0.111
L2D.Y	-0.061	-0.029	-0.088	-0.062
L3D.Y	0.117	0.214*	0.016	0.234**
L4D.Y	-0.071	-0.030	-0.131	-0.018
LD.SPINDEX*SPB	0.019	-0.526	0.088	0.100
L2D.SPINDEX*SPB	0.014	-0.200	0.166**	0.434
L3D.SPINDEX*SPB	0.050	-0.620	0.091	-0.208
L4D.SPINDEX*SPB	0.053	-0.809	0.073	-0.553
LD.ACREDIT*SPB	0.006	0.063*	-0.005	-0.017
L2D.ACREDIT*SPB	0.006	0.016	-0.020	-0.015
L3D.ACREDIT*SPB	0.034	-0.021	0.023	-0.025
L4D.ACREDIT*SPB	-0.024	-0.009	-0.028	0.015
LD.ACREDIT*nonSPB	0.007		0.005	
L2D.ACREDIT*nonSPB	0.004		0.004	
L3D.ACREDIT*nonSPB	0.043*		0.033	
L4D.ACREDIT*nonSPB	-0.020		-0.025	
LD.SPINDEX*nonSPB		0.031		0.112
L2D.SPINDEX*nonSPB		0.083		0.457
L3D.SPINDEX*nonSPB		-0.616		-0.128
L4D.SPINDEX*nonSPB		-0.893		-0.499
Constant	1.552	35.383	9.492	36.161
F tests:				
SP*SPB>AC		0.535		0.623
SP*nonSPB>AC		0.377		0.724
AC>SP*SPB	0.350		0.300	
AC>SP*nonSPB	0.193		0.295	

** p<0.05, ** p<0.01, *** p<0.001*

TABLE 12 ENGLE-GRANGER ERROR CORRECTION MODEL JAPAN STOCK PRICE BUBBLES

1. N: 146
2. Y corresponds to the dependent variable
3. The F test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations.
4. Lags are selected using the AIC selection criterion.
5. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
6. Spb1: stock price growth rate exceeds 15%. Spb2: deviation of 1 standard deviation from a smooth trend.

	Malaysia		**Belgium**		**Finland**		**France**		**Germany**		**Japan**		**Portugal**		**Netherlands**	
Causality	**SP>AC**	**AC>SP**	**SP>AC**	**AC>SP**	**SP>AC**	**AC>SP**	**SP>AC**	**AC>SP**	**SP>AC**	**AC>SP**	**SP>AC**	**AC>SP**	**SP>AC**	**AC>SP**	**SP>AC**	**AC>SP**
All sample	X*		X*			X*				X*			X**		X*	X*
SPB1			X*	X*		X**				X*					X*	X*
SPB2		X*		X*	X**	X*		X*	X**	X*						X*
nonSPB1	X*					X**		X**	X**						X*	X*
nonSPB2	X*		X**							X*						X*
ACB1	X*						O	O	O	O					X*	X**
ACB2	X*			X*	X**	X*		X*	X*							X*
nonACB1				X**		X*	O	O	O	O					X*	X*
nonACB2	X*								X**	X*					X**	X*
TB1		X**	O	O		X*	O	O	O	O					X*	
TB2		X*	O	O			O	O	O	O	O	O	O	O		X**
nonTB1	X**		O	O		X*	O	O	O	O					X*	X*
nonTB2	X*		O	O		X*	O	O	O	O	O	O	O	O	X*	X*

TABLE 13 OVERVIEW CAUSALITY INDIVIDUAL COUNTRY ANALYSIS.

1. VAR models for Malaysia, Belgium, Finland, France and Germany
2. VEC models for Japan, Engle-Granger error correction models for Portugal and the Netherlands.
3. Granger causality tests for VAR models, Wald F-tests for VECM and E/G ECM.
4. X indicates causality. O indicates omitted results as a consequence of no or too few bubble observations.
5. * P<0.05, ** P<0.10

5 Discussion

The following section discusses the results in relation to each individual hypothesis and the accompanying previous literatures regarding this hypothesis. Starting with the first two hypotheses tested with the panel analyses on the whole sample, then the third and fourth hypotheses tested with the panel analyses in bubble and non-bubble periods and then the last two hypotheses for the individual country effects. This chapter concludes with a discussion of the limitations of this study and suggestions for future research.

The results are partially in support of the first hypothesis, which states that credit has a positive effect on stock prices. That is, the F tests in both panel models indicate that there is a relationship between credit and stock prices. However, the coefficients of the lags of credit show different effects for the two estimators. As a result, one cannot conclude that credit has a positive effect on stock prices. In addition, only the DFE estimator indicates a long-run relationship from credit to stock prices. This can be due to the caveats of the GMM estimator, as it is not designed for a large-T small-N sample.

Hence, this study cannot confirm the theoretical models suggesting that more credit leads to higher stock prices (Miao & Wang, 2011; Mishkin, 2008). The results are also in contrast with empirical studies, as Goodhart et al. (2006) support this positive relationship when analysing individual countries and a panel. However, Goodhart et al. (2006) make use of an OLS regression to analyse the effect, which can be biased in time series. In addition, their sample only contains data until 2004, while this study analyses data until 2016.

The second hypothesis that stock prices have a positive effect on credit is also not fully supported. Only the DFE estimator provides results that indicate a relationship from stock prices to credit. In addition, the coefficients of stock prices in this regression are negative, which suggests a negative relationship between the variables. The DFE estimator also indicates a long-run relationship from stock prices to credit, which is not supported by the GMM estimator. Again, this can be due to the caveats of the GMM estimator in small-N samples.

Hence, this study cannot confirm the theoretical models suggesting that higher stock prices lead to more credit (Miao & Wang, 2011; Mishkin, 2008). This is also in contrast with Krainer (2014) and Goodhart et al. (2006), who find causality from stock prices to credit for individual countries and a panel. While this study does not support causality from stock prices to credit for each country, for the countries it does, the results indicate a positive relationship. However, both Goodhart et al. (2006) and Krainer (2014) apply an OLS regression model that can be biased for time series and only include data until 2004 and 2006, respectively. Hence, these confirmations do not add much value to the DFE results of this study.

The third hypothesis that bubbles affect the relationship from credit to stock prices is supported. As for both models, the F statistics indicate causality from credit to stock prices in credit bubbles. Moreover, the majority of the coefficients of credit in these stock price regressions are positive and significant. The F statistics also indicate causality from credit to stock prices in twin bubbles, were the majority of the coefficients is also positive. In contrast, there is weak evidence for causality from credit to stock prices in stock price bubbles, suggesting that this relationship merely occurs in credit bubbles. In addition, both estimators now indicate a long-run relationship from credit to stock prices.

This finding is in line with the theoretical models suggesting that credit bubbles lead to higher stock prices (Miao & Wang, 2011; Mishkin, 2008). This is the first study that analyses the relationship between credit bubbles and stock prices. To have some reference point, the results are compared with the relationship between credit bubbles and house prices (Shen et al., 2016). Shen et al. (2016) find no evidence for a relationship between credit and house prices in twin bubbles, using similar bubble definitions and a GMM estimator. This study shows that there is such a relationship between credit and stock prices, indicating that credit does not affect all prices in the same manner. However, Shen et al. (2016) study China, which can also explain the different findings as this credit market has different characteristics, (Allen, Qian, & Qian, 2005).

The results show ambiguous support for an effect of bubbles on the relationship from stock prices to credit, which is the fourth hypothesis. Only with the DFE estimator for the first stock price bubble definition, the F statistics indicate that the null hypothesis of no causality can be rejected with a reasonable confidence level. In twin bubbles, the DFE estimator suggests causality from stock prices to credit, while the majority of the coefficients in these relationships are positive. However, the GMM estimator does not confirm this. Remarkably, both estimators indicate causality from stock prices to credit in the first definition of credit bubbles and non-credit bubbles. Moreover, the coefficients of stock prices in credit bubbles are positive in this relationship. This suggests that in credit bubbles, stock prices fuel credit.

Thereby, this study provides mild empirical evidence for the theoretical models by Mishkin (2008) and Miao and Wang (2011) stating that stock prices lead to high credit levels. Moreover, these results are in line with Frömmel and Schmidt (2006), who indicate a positive relationship from stock prices to credit in periods of disequilibrium. However, their method does not analyse this relationship in true bubble periods, but periods of disequilibrium. The relationship from stock prices to credit in bubbles seems to be comparable with the relationship from house prices to credit in bubbles, as Shen et al. (2016) also show a positive relationship in bubbles that is mildly sensitive to the bubble definition.

The individual country analyses support the fifth hypothesis that relationship between stock prices and credit can differ between countries. This is shown by the whole country analyses and the impulse response functions. The traditional bank versus market-based diversion cannot explain this difference, as the relationship is different for Belgium, France, Germany, Japan and Portugal, while they are all bank-based countries.

This finding is expected (Krainer, 2014), but there are also differences with previous studies. This study only finds a positive two-way relationship in the Netherlands, while Goodhart et al. (2006) find a positive two-way relationship for Finland, Germany and the Netherlands. Again, this difference can be explained by the different sample period and method, as Goodhart et al. (2006) were only able to analyze data up to 2004 with OLS regressions, while this study includes data up to 2016 and VAR or VEC models. The finding of causality from stock prices to credit is expected for Malaysia (Krainer, 2014), but not for Belgium and Portugal (Frömmel & Schmidt, 2006). These contrasts can be attributed to the fact that Frömmel and Schmidt (2006) only analyze the relationship from credit to stock prices. In addition, the results fail to support the relationship from stock prices to credit for Japan, suggested by Kim & Moreno (1994). This can be explained, as they use a VAR model in their study, while this study uses a VEC model for Japan. Even though the cointegration tests suggest using a VEC model, a VAR model might be better, since the VEC results look spurious by not indicate a single relationship for Japan.

The individual country analyses also support the final hypothesis that the effect of bubbles on the relationships between stock prices and credit can differ across countries. This is shown by the results suggesting that credit affects stock prices in stock price bubbles only in Belgium, Finland, Germany and the Netherlands. While the whole country analyses also indicate causality from credit to stock prices in Finland, Germany and the Netherlands, they do not in Belgium. In addition, there is only strong evidence for causality from stock prices to credit in credit bubbles in Malaysia, but not in other countries.

These results are comparable to Frömmel and Schmidt's (2006) analyses of causality from credit to stock prices in disequilibrium. However, Frömmel and Schmidt (2006) also find this causality in Portugal and France, which is not supported by this study. As mentioned, Frömmel and Schmidt (2006) use a Markov-switching ECM model that is not suitable to analyze the relationship in bubble periods. Therefore, this is the first study that analyzes the effect of bubbles on the relationship between credit and stock prices by country.

There are some limitations to this study. First, credit bubbles usually flow to specific industries within a country, while this study only includes the country specific stock price indexes. As a result, the effect of credit to stock prices can sometimes disappear in the mass. Second, this study does not make a distinction between emerging and developed countries in the panel analysis, while they can differ. Moreover, the individual country analyses indicate that the relationship between stock prices and credit differs between countries. Therefore, a panel analysis can be less preferred. Third, the bubble periods are studied with singular observations, while periods make more sense. However, identifying bubble periods in the data is even more challenging, thus bubble periods can still lead to spurious results. Fourth, the models lack control variables, which increases the risk that both variables are explained by a common third variable. However, there will always be a possibility that an omitted variable causes the relationship. Therefore, one can argue that true causality can be measured in empirical studies. At last, the estimators come with some caveats. The GMM estimator is not designed for small-N, large-T samples (Roodman, 2006). The DFE estimator imposes restrictions on the error variances and the slope coefficient to be equal across all countries (Samargandi et al., 2015). The individual country VAR and VEC models can suffer from too few degrees of freedom. However, there may not be a perfect model without caveats.

Future work may consider certain factors to cope with the limitations or progress with these results. They may include industry specific stock price indices, focus merely on individual countries, identify and analyze periods of bubbles, and consider whether other factors can affect the relationship. In addition, the results indicate that the relationship differs between countries, thus studying other countries of interest is useful. At last, future studies may analyze if causality between stock prices and credit is stronger in bubble periods than in non-bubble periods.

6 Conclusion

This study analyses the relationship between the amount of credit and stock prices and shows how this relationship behaves in bubble and non-bubble periods. The analyses consist of both panel and individual country VEC or VAR models. The results of the whole sample analyses show that credit affects stock prices. Moreover, credit positively affects stock prices in the short-run in credit and twin bubbles. Stock prices also have a short-run effect on credit in credit bubbles. Thereby, the results indicate that the relationship can differ in the different bubbles periods and that a positive feedback loop can exist between credit and stock prices in credit bubbles. The bubble analyses also show a two-way long-run relationship between credit and stock prices. In addition, the individual country analyses indicate that the relationship between stock prices and credit can differ across countries. These results suggest two-way causality in the Netherlands, causality from stock prices to credit in Malaysia, Belgium and Portugal, and causality from credit to stock prices in Finland and Germany. Moreover, these results suggest that the effect of bubbles on these relationships differs across the countries. A possible explanation is that each country has its own unique characteristics, like regulations, rules and type of investors.

This study contributes to the existing literature in several ways. This is the first study that uses GMM and DFE estimators to analyze the relationship between stock prices and credit in panel data. These new estimators were used to shed light on the contradicting results from Krainer (2014) and Goodhart et al. (2006), but support neither of these studies by only indicating a one-way relationship between credit and stock prices in the whole sample. In addition, this is the first study that analyses the relationship between credit and stock prices in bubble periods using interaction variables. As mentioned, this study shows that the relationship between credit and stock prices can differ in the different bubbles. In fact, the results indicate a two-way relationship between stock prices and credit in credit bubbles. In addition, this study finds that the effect of bubbles can differ between countries. Where most previous studies focus on a sample until 2004, the sample in this study includes data until 2016. This is also a noticeable contribution, since many events have happened between 2004 and 2016 that could affect the relationship between stock prices and credit, like the credit crisis.

These new insights can be relevant for policy makers, investors, bankers and the public, as they all benefit from reductions in price bubbles. However, how these actors should treat bubbles is less straightforward. First of all, the relationship between the variables can differ between countries, requiring different actions in the different countries (Levieuge, 2017). Secondly, bubbles are very difficult to control, since bubbles can initiate because expectations about future performance change. It is very difficult to influence people's expectations, but presenting them with the consequences of their behavior and using contracts with back-loaded payments can help (Barlevy & Fisher, 2010). Bubbles can also start because of structural changes in regulation. Therefore, policy makers should at least consider the consequences of the new regulations and try to restrain the creation or risks of bubbles (Borio & Lowe, 2002). If bubbles already exist, it is unlikely that the existing regulations provide adequate restraints for the feedback loop. However, creating policies that restrict the creation of all bubbles might be wishful thinking. For example, to restrain credit bubbles, bank regulation should be separated from other markets and be based on a historical trend (Goodhart et al., 2004). Yet, this can also be subject to manipulation and is not necessarily more efficient (Mishkin, 2008). What might help in countries where credit raises stock prices is a policy that restricts leverage and margin requirements. This can help to restrain stock price bubbles (Neugebauer & Füllbrunn, 2013). In addition, implementing multiple different methods simultaneously is often also possible.

REFERENCES

Allen, F., & Gale, D. (2000a). Bubbles and Crises. *The Economic Journal*, *110*(460), 236–255.

Allen, F., & Gale, D. (2000b). Financial Contagion. *Journal of Political Economy*, *108*(1), 1–33. http://doi.org/10.1086/262109

Allen, F., & Gorton, G. (1993). Churning Bubbles. *Source: The Review of Economic Studies*, *60*(4), 813–836.

Allen, F., Qian, J., & Qian, M. (2005). Law, finance, and economic growth in China. *Journal of Financial Economics*, *77*, 57–116.

Almutair, S. (2015). Dynamics Of The Relationship Between Bank Loans And Stock Prices In Saudi Arabia. *International Business & Economics Research Journal*, *14*(3), 439–453.

Alshogeathri, M. A. M. (2011). *Macroeconomical determants of stock market movements: empirical evidence from the saudi stock market*. KANSAS STATE UNIVERSITY.

Anundsen, A. K., Gerdrup, K., Hansen, F., & Kragh-sørensen, K. (2016). Bubbles and crisis: the role of prices and credit. *J. Appl. EconJOURNAL OF APPLIED ECONOMETRICS*, *31*, 1291–1311. http://doi.org/10.1002/jae.2503

Arellano, M., & Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies*, *58*(2), 277–297.

Axelson, U., Jenkinson, T., Strömberg, P., & Weisbach, M. S. (2013). Borrow Cheap, Buy High? The Determinants of Leverage and Pricing in Buyouts. *Journal of Finance*, *68*(6), 2223–2267. http://doi.org/10.1111/jofi.12082

Barajas, A., Dell' Ariccia, G., & Levchenko, A. (2007). Credit booms: the good, the bad and the ugly. *International Monetary Fund*.

Barlevy, G. ;, & Fisher, J. D. M. (2010). Mortgage Choices and Housing Speculation;, 2010–12.

Beck, T., & Levine, R. (2002). *STOCK MARKETS, BANKS, AND GROWTH: PANEL EVIDENCE* (Working Paper 9082). Cambridge.

Bernanke, B. S., Gertler, M., & Gilchrist, S. (1999). *The financial accelerator in a quantitative business cycle framework*. (J.B. Taylor and M. Woodford, Ed.)*handbook of Macroeconomics* (Vol. 1). Elsevier Science B.V.

Blackburne, E. F., & Frank, M. W. (2007). Estimation of nonstationary hetergoeneous panels.

Stata Journal, *7*(2), 197–208.

Borio, C., & Lowe, P. (2002). Asset prices, financial and monetary stability: exploring the nexus. *BIS Working Paper*, (114), 47. http://doi.org/10.2139/ssrn.846305

Brunnermeier, M. K., & Oehmke, M. (2012). *Bubbles, financial crises, and systemic risk*.

Christiano, L., Ilut, C., Motto, R., & Rostagno, M. (2010). Monetary Policy and Stock Market Booms. National Bureau of Economic Research.

Claessens, S., Kose, M. A., & Terrones, M. E. (2010). Financial Cycles: What? How? When? In Richard Clarida and Francesco Giavazzi (Ed.), *NBER International Seminar on Macroeconomics 2010* (pp. 303–343). University of Chicago Press.

Claessens, S., Köse, M. A., & Terrones, M. E. (2010). *The global financial crisis: how similar? How different? How costly?* (No. 1011). Istanbul.

Cochrane, J. H. (2002). Stocks as Money: Convenience Yield and the Tech-Stock Bubble. In *Chicago Conference on Asset Price Bubbles* (p. 30). Chicago.

Doblas-Madrid, A. (2012). A robust model of bubbles with multidimensional uncertainty. *Econometrica*, *80*(5), 1845–1893.

Drehmann, M., Borio, C., & Tsatsaronis, K. (2012). Characterising the Financial Cycle: Don't Lose Sight of the Medium Term! *BIS Working Papers*, (380), 1–38. http://doi.org/DOI:

Engle, R. F., & Granger, C. W. J. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. *Source: Econometrica Econometrica*, *55*(2), 251–276.

Foresti, P. (2006). Testing for Granger causality between stock prices and economic growth. MPRA Paper No. 2962.

Frömmel, M., & Schmidt, T. (2006). *Bank Lending and Asset Prices in the Euro Area* (No. 42).

Geanakoplos, J. (2010). The Leverage Cycle. *NBER Macroeconomics Annual*, *24*(1), 1–66. http://doi.org/10.1086/648285

Goodhart, C., Basurto, M. A. S., & Hofmann, B. (2006). *Default, Credit Growth, and Asset Prices*.

Goodhart, C., & Hofmann, B. (2008). House prices, money, credit, and the macroeconomy. *Oxford Review of Economic Policy*, *24*(1), 180–205. http://doi.org/10.1093/oxrep/grn009

Goodhart, C., Hofmann, B., & Segoviano, M. (2004). Bank regulation and macroeconomical fluctuation. *Oxford Review of Economic Policy*, *20*(4), 591–615. http://doi.org/10.1093/oxrep/grh034

Gourinchas, P.-O., Valdes, R., & Landerretche, O. (2001). *Lending booms: lating America and the world* (No. 8249).

Guo, F., & Huang, Y. S. (2009). Does hot money'' drive China's real estate and stock markets? *International Review of Economics and Finance*, *19*, 452–466. http://doi.org/10.1016/j.iref.2009.10.014

Herrera, S., & Perry, G. (2001). *Tropical Bubbles: Asset Prices in Latin America, 1980-2001* (No. 2724).

Hodrick, R. J., & Prescott, E. C. (1997). Postwar U . S . Business Cycles : An Empirical Investigation. *Journal of Money, Credit and Banking*, *29*(1), 1–16.

Ibrahim, M. H. (2006). Stock prices and bank loan dynamics in a developing country: the case of Malaysia. *Journal of Applied Economics*, *9*(1), 71–89.

International Moneatry Fund, I. (2004). *World Economic Outlook Advancing Structural Reforms*. *Office*.

Jordà, Ò., Schularick, M., & Taylor, A. M. (2015). *Leveraged Bubbles*. Munich.

Kim, S. B., & Moreno, R. (1994). Stock prices and bank lending behavior in Japan. *Economic Review*. Federal Reserve Bank of San Francisco.

Krainer, R. E. (2014). Monetary policy and bank lending in the Euro area: Is there a stock market channel or an interest rate channel? *Journal of International Money and Finance*, *49*, 283–298. http://doi.org/10.1016/j.jimonfin.2014.03.009

Kuttner, K. N. (2012). Low Interest Rates and Housing Bubbles: Still No Smoking Gun. In *The Role of Central Banks in Financial Stability: How Has It Changed?* (p. 27). Williamstown.

Levieuge, G. (2017). Explaining and forecasting bank loans. Good times and crisis. *Applied Economics*, *49*(8), 823–843. http://doi.org/10.1080/00036846.2016.1208350

Levine, R., & Zervos, S. (1998). Stock Markets, Banks, and Economic Growth. *The American Economic Review*, *88*(3), 537–558.

Mendoza, E. G., & Terrones, M. E. (2008). *An Anatomy Of Credit Booms: Evidence From Macro Aggregates And Micro Data* (NBER working paper series No. 14049). Cambridge.

Miao, J., & Wang, P. (2011). Bubbles and Credit Constraints.

Michailova, J. (2011). Overconfidence and bubbles in experimental asset markets. *MPRA Paper No. 30579*.

Minsky, H. P. (1977). The financial instability hypothesis: an interpretation of Keynes and an alternative to standard theory. *Nebraska Journal of Economics and Business*, *16*(1), 5–16.

Mishkin, F. S. (2008). How should we respond to asset price bubbles? *Banque de France Financial Stability Review*, *12*, 65–73.

Neugebauer, T., & Füllbrunn, S. (2013). *Deflating Bubbles in Experimental Asset Markets : Comparative Statics of Margin Regulations* (No. No. 13-14).

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, *94*(446), 621–634.

Ratanapakorn, O., & Sharma, S. C. (2007). Dynamic analysis between the US stock returns and the macroeconomic variables. *Applied Financial Economics*, *17*(5), 369–377. http://doi.org/10.1080/09603100600638944

Roodman, D. (2006). *How to Do xtabond2: An Introduction to "Difference" and "System" GMM in Stata* (No. 103).

Samargandi, N., Fidrmuc, J., & Ghosh, S. (2015). Is the Relationship between Financial Development and Economic Growth Monotonic? Evidence from a Sample of Middle Income Countries. *World Development*, *68*, 66–81.

Senhadji, A. S., & Collyns, C. (2002). *Lending booms, real estate bubbles and the Asian crisis*.

Shen, C.-H., Lee, Y. H., Wu, M.-W., & Guo, N. (2016). Does housing boom lead to credit boom or is it the other way around? The case of China. *International Review of Economics and Finance*, *42*, 349–367. http://doi.org/10.1016/j.iref.2015.10.008

Yartey, C. A. (2008). *The Determinants of Stock Market Development in Emerging Economies: Is South Africa Different?* (No. WP/08/32).

Appendix 1 – Descriptive statistics

ncountry	variable	N	mean	sd	min	max
MALAYSIA	ΔSPINDEX	114	4.178342	34.38415	-105.732	93.984
	ΔACREDIT	105	3.079142	10.51707	-44.71257	31.08795
JAPAN	ΔSPINDEX	145	3.724035	82.99747	-308.293	220.732
	ΔACREDIT	145	44.33175	400.9654	-1202.411	1192.157
PORTUGAL	ΔSPINDEX	114	-.238158	15.49543	-45.817	50.745
	ΔACREDIT	145	2.34531	4.155718	-7.76	23.38
BELGIUM	ΔSPINDEX	145	7.803655	73.10964	-350.197	191.323
	ΔACREDIT	145	5.830103	7.165614	-10.457	49.944
FINLAND	ΔSPINDEX	138	4.285862	108.8374	-491.354	702.555
	ΔACREDIT	145	2.444648	3.240603	-10.874	11.534
NETHERLANDS	ΔSPINDEX	145	8.604365	75.24337	-363.053	244.31
	ΔACREDIT	145	9.990455	12.00558	-20.68	52.001
FRANCE	ΔSPINDEX	145	10.00215	95.42082	-402.464	272.197
	ΔACREDIT	145	25.20572	18.34367	-12.776	80.736
GERMANY	ΔSPINDEX	145	5.43371	52.94089	-184.401	210.07
	ΔACREDIT	145	17.3857	20.17025	-54.768	69.722

TABLE 14 BASIC STATISTICS PER COUNTRY

Notes: 1. SPINDEX refers to MSCI stock price index, ACREDIT refers to all credit to the private sector
2. T = 146 (Q2 1980 – Q3 2016), but missing values for Malaysia, Portugal and Finland
3. Mean ΔSPINDEX is mean change of index.
4. Mean ΔACREDIT is mean change of ACREDIT in billion euros.

	spb1	*spb2*	*acb1*	*acb2*	*tb1*	*tb2*
1980	0	6	0	0	0	0
1981	4	1	7	0	3	0
1982	7	0	10	0	3	0
1983	19	0	10	2	5	0
1984	18	2	8	8	3	0
1985	13	2	3	3	1	0
1986	18	7	3	0	2	0
1987	14	9	1	0	1	0
1988	11	2	7	0	2	0
1989	25	10	5	0	3	0
1990	9	10	6	3	3	0
1991	2	0	11	1	0	0
1992	5	0	6	4	1	0
1993	18	1	14	9	9	0
1994	19	7	3	2	3	0
1995	1	0	3	2	0	0
1996	19	3	5	2	4	2
1997	25	5	3	3	1	3
1998	22	9	4	0	4	0
1999	15	4	7	1	3	0
2000	21	24	11	9	6	7
2001	0	11	3	14	0	6
2002	1	0	0	5	0	0
2003	4	0	0	0	0	0
2004	19	0	0	1	0	0
2005	13	0	1	0	0	0
2006	22	13	1	0	0	0
2007	19	30	0	0	0	0
2008	2	12	2	4	0	0
2009	3	0	3	5	0	0
2010	20	0	6	2	4	0
2011	5	0	0	2	0	0
2012	4	0	3	2	0	0
2013	21	0	0	0	0	0
2014	6	1	2	0	0	0
2015	20	4	2	1	0	0
2016	0	0	2	1	0	0
Total	444	173	152	86	61	18

TABLE 15 NUMBER OF QUARTALS WITH BUBBLES BY YEAR

Notes: 1. Spb1: stock price growth rate exceeds 15%. Spb2: deviation of 1 standard deviation from a smooth trend.
2. Acb1: credit growth rate exceeds 15%. Acb2: deviation of 1.5 standard deviation from a smooth trend.
3. Tb1: twin boom 1, which denotes that stock price boom and credit boom occur simultaneously. Tb1 = spb1 * acb1, tb2 = spb2 * acb2.
4. Year: denotes sum of bubbles of all quarters and all countries for that year. Exceptions: 1980 only Q2 – Q4, 2016 only Q1-Q3.

ncountry	variable	N	mean	sd	min	max
MALAYSIA	ΔSPINDEX	101	-.1097226	33.29175	-105.732	80.947
	ΔACREDIT	92	2.168047	10.3995	-44.71257	31.08795
JAPAN	ΔSPINDEX	122	-4.180443	84.87065	-308.293	220.732
	ΔACREDIT	122	6.253011	396.4727	-1202.411	1192.157
PORTUGAL	ΔSPINDEX	103	-1.102903	14.32085	-45.817	35.318
	ΔACREDIT	134	2.229179	4.249538	-7.76	23.38
BELGIUM	ΔSPINDEX	144	7.559111	73.30529	-350.197	191.323
	ΔACREDIT	144	5.856951	7.183302	-10.457	49.944
FINLAND	ΔSPINDEX	128	4.413047	113.0284	-491.354	702.555
	ΔACREDIT	135	2.454274	3.347977	-10.874	11.534
NETHERLANDS	ΔSPINDEX	142	7.866479	75.81944	-363.053	244.31
	ΔACREDIT	142	9.461993	11.52255	-20.68	52.001
FRANCE	ΔSPINDEX	145	10.00215	95.42082	-402.464	272.197
	ΔACREDIT	145	25.20572	18.34367	-12.776	80.736
GERMANY	ΔSPINDEX	145	5.43371	52.94089	-184.401	210.07
	ΔACREDIT	145	17.3857	20.17025	-54.768	69.722
Total	ΔSPINDEX	1030	4.246531	75.98716	-491.354	702.555
	ΔACREDIT	1059	9.400495	134.8304	-1202.411	1192.157

TABLE 16 BASIC STATISTICS BY COUNTRY AND NO TB1

Notes: 1. The values of ΔSPINDEX refer to index points and of ΔACREDIT refer to billion euros.
2. Only includes observations of no twin bubbles 1, which is exactly the opposite of Table 16.

ncountry	variable	N	mean	sd	min	max
MALAYSIA	ΔSPINDEX	13	37.49331	23.23211	2.473	93.984
	ΔACREDIT	13	9.526892	9.331262	-.8205133	28.15222
JAPAN	ΔSPINDEX	23	45.65213	57.34006	-63.125	187.258
	ΔACREDIT	23	246.3147	370.2615	-509.6211	1042.071
PORTUGAL	ΔSPINDEX	11	7.859	23.27052	-27.186	50.745
	ΔACREDIT	11	3.76	2.475217	.52	8.236
BELGIUM	ΔSPINDEX	1	43.018	.	43.018	43.018
	ΔACREDIT	1	1.964	.	1.964	1.964
FINLAND	ΔSPINDEX	10	2.6579	6.12273	-6.664	12.09
	ΔACREDIT	10	2.3147	1.056028	1.165	4.13
NETHERLANDS	ΔSPINDEX	3	43.531	22.10798	18.659	60.947
	ΔACREDIT	3	35.00433	7.683429	26.422	41.243
Total	ΔSPINDEX	61	29.90248	41.9308	-63.125	187.258
	ΔACREDIT	61	97.71427	252.8293	-509.6211	1042.071

TABLE 17 BASIC STATISTICS BY COUNTRY AND TB1

Notes: 1. The values of ΔSPINDEX refer to index points and of ΔACREDIT refer to billion euros.
2. Only includes observations of twin bubbles 1, which is exactly the opposite of Table 15.
3. France and Germany are excluded because for these countries no twin bubble 1 observation is found.

ncountry	variable	N	mean	sd	min	max
MALAYSIA	ΔSPINDEX	109	4.921642	34.23941	-105.732	93.984
	ΔACREDIT	100	3.001594	10.1757	-44.71257	31.08795
JAPAN	ΔSPINDEX	142	3.882239	83.13893	-308.293	220.732
	ΔACREDIT	142	42.03261	398.7281	-1202.411	1192.157
PORTUGAL	ΔSPINDEX	114	-.238158	15.49543	-45.817	50.745
	ΔACREDIT	145	2.34531	4.155718	-7.76	23.38
BELGIUM	ΔSPINDEX	145	7.803655	73.10964	-350.197	191.323
	ΔACREDIT	145	5.830103	7.165614	-10.457	49.944
FINLAND	ΔSPINDEX	134	10.85533	96.4383	-355.777	702.555
	ΔACREDIT	141	2.361943	3.205732	-10.874	11.534
NETHERLANDS	ΔSPINDEX	140	10.10424	75.20034	-363.053	244.31
	ΔACREDIT	140	9.42255	11.50296	-20.68	52.001
FRANCE	ΔSPINDEX	144	10.59604	95.48458	-402.464	272.197
	ΔACREDIT	144	25.04081	18.29951	-12.776	80.736
GERMANY	ΔSPINDEX	145	5.43371	52.94089	-184.401	210.07
	ΔACREDIT	145	17.3857	20.17025	-54.768	69.722
Total	ΔSPINDEX	1073	6.873293	72.54606	-402.464	702.555
	ΔACREDIT	1102	13.82325	143.77	-1202.411	1192.157

TABLE 18 BASIC STATISTICS BY COUNTRY AND NO TB2

Note: 1. The values of ΔSPINDEX refer to index points and of ΔACREDIT refer to billion euros.
2. Only includes observations of no twin bubbles 2, which is exactly the opposite of Table 18.

ncountry	variable	N	mean	sd	min	max
MALAYSIA	ΔSPINDEX	5	-12.0256	37.45347	-52.123	35.229
	ΔACREDIT	5	4.630098	17.60484	-25.13764	21.37987
JAPAN	ΔSPINDEX	3	-3.764333	92.68309	-105.893	75.003
	ΔACREDIT	3	153.1581	590.8934	-509.6211	624.8965
FINLAND	ΔSPINDEX	4	-215.7913	249.2515	-491.354	-3.358
	ΔACREDIT	4	5.36	3.583058	3.119	10.698
NETHERLANDS	ΔSPINDEX	5	-33.3922	70.84155	-111.968	58.272
	ΔACREDIT	5	25.8918	16.22982	11.234	45.687
FRANCE	ΔSPINDEX	1	-75.518	.	-75.518	-75.518
	ΔACREDIT	1	48.954	.	48.954	48.954
Total	ΔSPINDEX	18	-65.3925	143.6049	-491.354	75.003
	ΔACREDIT	18	37.91543	210.1971	-509.6211	624.8965

TABLE 19 BASIC STATISTICS BY COUNTRY AND TB2

Note: 1. The values of ΔSPINDEX refer to index points and of ΔACREDIT refer to billion euros.
2. Only includes observations of twin bubbles 2, which is exactly the opposite of Table 17.
3. Portugal, Belgium and Germany are excluded because for these countries no twin bubble 2 observation is found.

Appendix 2 – Panel error correction models

	Reg		Panel Reg		GMM	
	ΔSPINDEX	ΔCREDIT	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
LD.SPINDEX	0.197***	0.003	0.196***	0.003	0.135*	-0.014
L2D.SPINDEX	0.023	0.012	0.022	0.011	-0.072	-0.023
LD.ACREDIT	0.000	0.120***	0.000	0.113***	-0.056*	0.117***
L2D.ACREDIT	0.002	-0.035	0.002	-0.041	-0.049**	-0.039**
qdate	-0.036	-0.135	-0.031	-0.113	-2.050	-0.113
ECM					0.073	-0.018
_cons	10.229	34.678	9.385	31.455	349.144	29.221

* p<0.05, ** p<0.01, *** p<0.001

TABLE 20 COMPARISON COEFFICIENTS FOR VALIDITY GMM

Note: Comparison GMM estimator with normal and panel regression as the coefficients should match for validity of the GMM model (Roodman, 2006)

	ACB1		ACB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
LD.SPINDEX*ACB	-2.360*	0.855	-0.265*	0.169
L2D.SPINDEX*ACB	-0.710	1.072	-0.700***	0.077
LD.ACREDIT*ACB	0.186	0.042	-0.258***	-0.455**
L2D.ACREDIT*ACB	0.268*	0.182*	0.089	-0.165
LD.SPINDEX*nonACB	0.301	-0.093	0.335***	-0.074
L2D.SPINDEX*nonACB	0.035	-0.185	0.402***	-0.051
LD.ACREDIT*nonACB	-0.053	0.118**	0.076**	0.285***
L2D.ACREDIT*nonACB	-0.255*	-0.149**	0.002	0.002
ECM	-0.039	-0.035**	-0.088***	-0.012
qdate	-0.003	0.184	0.249**	0.014
_cons	-0.612	-16.159	-40.434**	14.277
Test statistics:				
AR(1): Pr > z=	0.107	.	.	.
AR(2): Pr > z=	0.145	0.098	0.213	0.266
Sargan: Prob > chi2=	0.446	0.081	0.000	0.000
Sample:				
Observations	1066	1066	1066	1066
Groups	8	8	8	8
Instruments	21.000	12.000	25.000	13.000
F tests:				
F value	0.097	0.000	0.000	0.000
SP*ACB>AC		0.018		0.739
SP*nonACB>AC		0.042		0.679
AC*ACB>SP	0.071		0.000	
AC*nonACB>SP	0.070		0.009	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 21 PANEL ERROR CORRECTION MODEL DURING CREDIT BOOMS (GMM)

Notes: 1. ACB1: credit growth rate exceeds 15%. ACB2: deviation of 1.5 standard deviation from a smooth trend.
2. Arellano and Bond's GMM estimator
3. F value is the joint test examining the null hypothesis that the coefficients do not Granger cause y.
4. F SP>AC (F AC>SP) is the tests examining the null hypothesis that the coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) by bubble and non-bubble observations. The coefficients indicate the direction of the effect.
5. ECM is an error correction term.
6. AR tests H(0): no autocorrelation with the error
7. Sargan and Hansen H(0): instruments are not valid.

	TB1		TB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
LD.SPINDEX*TB	-1.431**	1.157	-0.811**	-0.189
L2D.SPINDEX*TB	-0.458	1.835	0.742***	-0.607
LD.ACREDIT*TB	-0.120	-0.448	0.287	-4.315***
L2D.ACREDIT*TB	0.426***	0.600*	0.330	2.006***
LD.SPINDEX*nonTB	0.315***	-0.038	0.354***	-0.058
L2D.SPINDEX*nonTB	-0.017	-0.112	-0.080	0.063
LD.ACREDIT*nonTB	0.004	0.090*	-0.006	0.321***
L2D.ACREDIT*nonTB	-0.030	-0.150***	-0.027	-0.014
ECM	-0.069***	-0.027*	-0.049*	-0.041**
qdate	0.212**	0.125	0.128	0.198
_cons	-29.327*	-9.063	-17.956	-20.357
Test statistics:				
AR(1): Pr > z=	0.000	0.000	0.000	0.000
AR(2): Pr > z=	0.162	0.347	0.123	.
Sargan: Prob > chi2=	0.000	0.000	0.007	0.021
Sample:				
Observations	1066	1066	1066	1066
Groups	8	8	8	8
Instruments	24.000	16.000	25.000	17.000
F tests:				
F value	0.000	0.000	0.000	0.000
SP*TB>AC		0.419		0.465
SP*nonTB>AC		0.212		0.707
AC*TB>SP	0.000		0.063	
AC*nonTB>SP	0.303		0.516	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 22 PANEL ERROR CORRECTION MODEL DURING TWIN BOOMS (GMM)

Notes: 1. Tb1: twin boom 1, which denotes that stock price boom and credit boom occur simultaneously. Tb1 = spb1 * acb1, tb2 = spb2 * acb2.
2. Arellano and Bond's GMM estimator
3. F value is the joint test examining the null hypothesis that the coefficients do not Granger cause y.
4. F SP>AC (F AC>SP) is the tests examining the null hypothesis that the coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) by bubble and non-bubble observations. The coefficients indicate the direction of the effect.
5. ECM is an error correction term.
6. AR tests H(0): no autocorrelation with the error
7. Sargan and Hansen H(0): instruments are not valid.

	SPB1		SPB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
LD.SPINDEX*SPB	0.258***	-0.138	0.154*	-0.031
L2D.SPINDEX*SPB	0.029	-0.116	0.143	-0.037
LD.ACREDIT*SPB	0.013	0.131***	0.000	-0.688***
L2D.ACREDIT*SPB	0.040***	0.209***	0.044	0.042***
ECM	-0.051***	-0.033***	-0.051***	-0.023***
LD.SPINDEX*nonSPB	0.177***	0.045	0.252***	-0.024
L2D.SPINDEX*nonSPB	0.066**	-0.006	0.008	-0.016
LD.ACREDIT*nonSPB	0.003*	0.105***	0.009***	0.193***
L2D.ACREDIT*nonSPB	-0.004	-0.136***	0.007	-0.077***
qdate	0.305**	0.110*	0.300**	-0.059
_cons	-11.302	21.953*	-10.777	32.879**
F tests:				
F value	0.000	0.000	0.000	0.000
F SP*SPB>AC		0.063		0.420
F SP*nonSPB>AC		0.108		0.004
F AC*SPB>SP	0.000		0.000	
F AC*nonSPB>SP	0.021		0.001	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 23 PANEL ERROR CORRECTION MODEL DURING STOCK PRICE BOOMS (DFE)

Notes: 1. SPB1: stock price growth rate exceeds 15%. SPB2: deviation of 1 standard deviation from a smooth trend.
2. Cross country dynamic fixed effects estimator (DFE)
3. F value is the joint test examining the null hypothesis that the coefficients do not Granger cause y.
4. F SP>AC (F AC>SP) is the tests examining the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) by bubble and non-bubble observations. The coefficients indicate the direction of the effect.
5. ECM is an error correction term.
6. N: 1066

	ACB1		ACB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
LD.SPINDEX*ACB	0.099	0.344	0.162	0.268
L2D.SPINDEX*ACB	0.317	0.370	0.235	0.114
LD.ACREDIT*ACB	0.031***	0.080***	-0.045*	-0.281***
L2D.ACREDIT*ACB	0.048***	0.138***	-0.023	-0.199***
ECM	-0.050***	-0.032***	-0.049***	-0.015***
LD.SPINDEX*nonACB	0.226***	-0.073	0.223***	-0.078
L2D.SPINDEX*nonACB	0.024	-0.077	0.016	-0.031**
LD.ACREDIT*nonACB	-0.011***	0.134***	0.012*	0.188***
L2D.ACREDIT*nonACB	-0.018***	-0.137***	0.021***	0.033***
qdate	0.322***	0.160	0.280**	-0.004
_cons	-13.232	13.788	-10.203	22.685***
F tests:				
F value	0.000	0.000	0.000	0.000
F SP*ACB>AC		0.081		0.693
F SP*nonACB>AC		0.041		0.009
F AC*ACB>SP	0.000		0.029	
F AC*nonACB>SP	0.000		0.000	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 24 PANEL ERROR CORRECTION MODEL DURING CREDIT BOOMS (DFE)

Notes: 1. ACB1: credit growth rate exceeds 15%. ACB2: deviation of 1.5 standard deviation from a smooth trend.
2. Cross country dynamic fixed effects estimator (DFE)
3. F value is the joint test examining the null hypothesis that the coefficients do not Granger cause y.
4. F SP>AC (F AC>SP) is the tests examining the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) by bubble and non-bubble observations. The coefficients indicate the direction of the effect.
5. ECM is an error correction term.
6. N: 1066

	TB1		TB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
LD.SPINDEX*TB	0.295	-0.540*	0.021	0.132
L2D.SPINDEX*TB	0.214**	0.033	0.695***	0.112***
LD.ACREDIT*TB	-0.001	0.113***	0.070	-1.592***
L2D.ACREDIT*TB	0.017*	0.264***	0.016	-0.106***
ECM	-0.051***	-0.033***	-0.041***	-0.024***
LD.SPINDEX*nonTB	0.213***	-0.017*	0.232***	-0.060
L2D.SPINDEX*nonTB	0.048	-0.054	-0.014	-0.039***
LD.ACREDIT*nonTB	0.007***	0.126***	-0.001	0.167***
L2D.ACREDIT*nonTB	0.004	-0.100***	0.012***	-0.059***
qdate	0.305**	0.082	0.254**	-0.060
_cons	-11.849	25.125*	-6.985	32.188***
F tests:				
F value	0.000	0.000	0.000	0.000
F SP*TB>AC		0.000		0.000
F SP*nonTB>AC		0.068		0.000
F AC*TB>SP	0.000		0.000	
F AC*nonTB>SP	0.000		0.000	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 25 PANEL ERROR CORRECTION MODEL DURING TWIN BOOMS (DFE)

Notes: 1. Tb1: twin boom 1, which denotes that stock price boom and credit boom occur simultaneously. Tb1 = spb1 * acb1, tb2 = spb2 * acb2.
2. Cross country dynamic fixed effects estimator (DFE).
3. F value is the joint test examining the null hypothesis that the coefficients do not Granger cause y.
4. F SP>AC (F AC>SP) is the tests examining the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) by bubble and non-bubble observations. The coefficients indicate the direction of the effect.
5. ECM is an error correction term.
6. N: 1066

Appendix 3 – country level analysis

Augmented Dickey-Fuller tests

	SPINDEX	ΔSPINDEX	ACREDIT	ΔACREDIT
Malaysia				
Zt	-1.725	-4.523	-1.054	-3.762
P	0.740	0.001	0.936	0.019
Japan				
Zt	-3.117	-3.698	-1.792	-3.939
P	0.102	0.023	0.708	0.011
Portugal				
Zt	-1.790	-3.592	-2.217	-3.676
P	0.709	0.031	0.480	0.024
Belgium				
Zt	-3.202	-3.307	-1.406	-4.022
P	0.084	0.015	0.859	0.008
Finland				
Zt	-1.868	-3.606	-2.058	-3.875
P	0.347	0.006	0.569	0.013
Netherlands				
Zt	-1.317	-3.169	-2.209	-3.328
P	0.621	0.022	0.485	0.014
France				
Zt	-2.445	-3.746	-1.218	-3.732
P	0.356	0.020	0.907	0.004
Germany				
Zt	-3.033	-3.785	-1.764	-4.698
P	0.123	0.017	0.722	0.001

TABLE 26 AUGMENTED DICKEY-FULLER TEST RESULTS PER COUNTRY

Note: ADF test: Zt: statistic, P is probability Zt is larger than the ADF 5% critical value

Johansen tests for cointegration

Trend: trend Number of obs = 99
Sample: 1992q1 - 2016q3 Lags = 7

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	28	-844.98819	.	11.5426*	18.17
1	31	-839.88508	0.09796	1.3363	3.74
2	32	-839.21691	0.01341		

TABLE 27 COINTEGRATION TEST RESULTS MALAYSIA

Note: Cointegration if trace statistic is smaller than the 5% critical value, indicated with *.

Johansen tests for cointegration

Trend: constant Number of obs = 141
Sample: 1981q3 - 2016q3 Lags = 5

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	18	-1858.4711	.	15.6799	15.41
1	21	-1854.0763	0.06043	6.8903	3.76
2	22	-1850.6311	0.04769		

TABLE 28 COINTEGRATION TEST RESULTS JAPAN

Note: Cointegration if trace statistic is smaller than the 5% critical value, indicated with *.

Johansen tests for cointegration

Trend: constant Number of obs = 111
Sample: 1989q1 - 2016q3 Lags = 4

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	14	-764.26344	.	24.9174	15.41
1	17	-752.86105	0.18572	2.1126*	3.76
2	18	-751.80477	0.01885		

TABLE 29 COINTEGRATION TEST RESULTS PORTUGAL

Note: Cointegration if trace statistic is smaller than the 5% critical value, indicated with *.

Johansen tests for cointegration

Trend: trend Number of obs = 137
Sample: 1982q3 - 2016q3 Lags = 9

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	36	-1191.7646	.	14.1613*	18.17
1	39	-1185.0409	0.09349	0.7139	3.74
2	40	-1184.6839	0.00520		

TABLE 30 COINTEGRATION TEST RESULTS BELGIUM

Note: Cointegration if trace statistic is smaller than the 5% critical value, indicated with *.

```
                     Johansen tests for cointegration
Trend: trend                                       Number of obs =     136
Sample:  1982q4 - 2016q3                                    Lags =       3
-------------------------------------------------------------------------------
                                                            5%
maximum                                        trace    critical
  rank    parms       LL       eigenvalue  statistic    value
    0      12     -1166.5803         .      14.7390*    18.17
    1      15     -1159.9409     0.09302     1.4602      3.74
    2      16     -1159.2108     0.01068
-------------------------------------------------------------------------------
```

TABLE 31 COINTEGRATION TEST RESULTS FINLAND

Note: Cointegration if trace statistic is smaller than the 5% critical value, indicated with *.

```
                     Johansen tests for cointegration
Trend: trend                                       Number of obs =     141
Sample:  1981q3 - 2016q3                                    Lags =       5
-------------------------------------------------------------------------------
                                                            5%
maximum                                        trace    critical
  rank    parms       LL       eigenvalue  statistic    value
    0      20     -1322.8339         .      28.8832     18.17
    1      23     -1311.2714     0.15126     5.7582      3.74
    2      24     -1308.3924     0.04002
-------------------------------------------------------------------------------
```

TABLE 32 COINTEGRATION TEST RESULTS NETHERLANDS

Note: Cointegration if trace statistic is smaller than the 5% critical value, indicated with *.

```
                     Johansen tests for cointegration
Trend: trend                                       Number of obs =     130
Sample:  1984q2 - 2016q3                                    Lags =      16
-------------------------------------------------------------------------------
                                                            5%
maximum                                        trace    critical
  rank    parms       LL       eigenvalue  statistic    value
    0      64     -1256.7873         .      15.0373*    18.17
    1      67       -1249.51     0.10592     0.4826      3.74
    2      68     -1249.2687     0.00371
-------------------------------------------------------------------------------
```

TABLE 33 COINTEGRATION TEST RESULTS FRANCE

Note: Cointegration if trace statistic is smaller than the 5% critical value, indicated with *.

```
                     Johansen tests for cointegration
Trend: trend                                       Number of obs =     140
Sample:  1981q4 - 2016q3                                    Lags =       6
-------------------------------------------------------------------------------
                                                            5%
maximum                                        trace    critical
  rank    parms       LL       eigenvalue  statistic    value
    0      24     -1340.0518         .      17.3753*    18.17
    1      27      -1332.943     0.09657     3.1579      3.74
    2      28     -1331.3641     0.02230
-------------------------------------------------------------------------------
```

TABLE 34 COINTEGRATION TEST RESULTS GERMANY

Note: Cointegration if trace statistic is smaller than the 5% critical value, indicated with *.

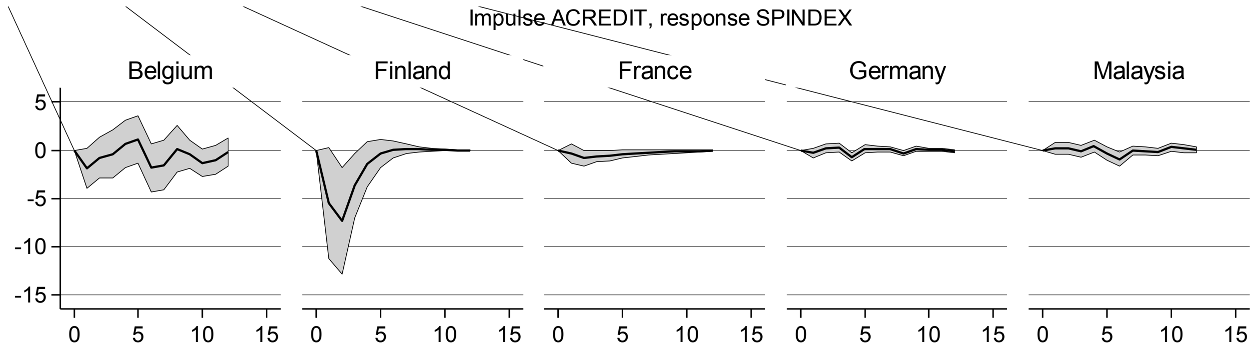


FIGURE 10 IRF VAR MODELS, RESPONSE ΔSPINDEX

Note: IRF indicates how the response variable reacts to a shock in the impulse variable, thereby suggesting a causal relationship. This model is based on the VAR results of the whole country analysis for each respective country. The black line indicates the response; the grey areas indicate the 95% confidence interval.

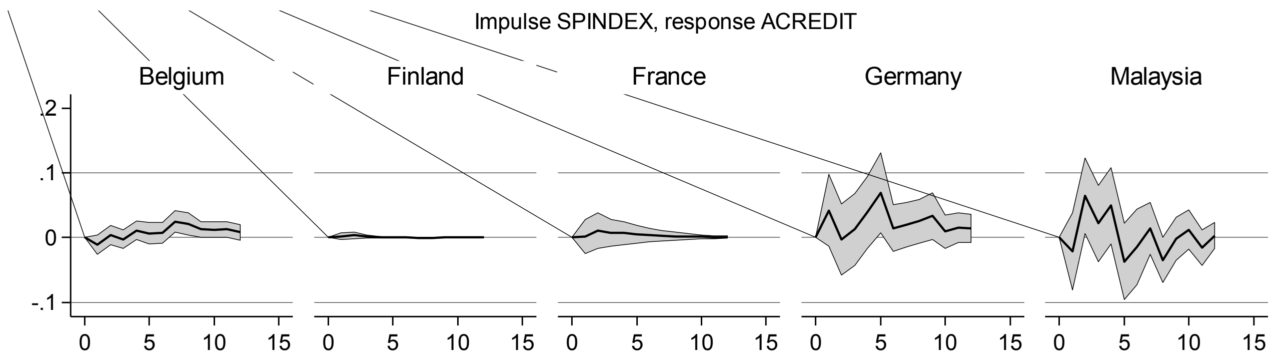


FIGURE 11 IRF VAR MODELS, RESPONSE ΔACREDIT

Note: IRF indicates how the response variable reacts to a shock in the impulse variable, thereby suggesting a causal relationship. This model is based on the VAR results of the whole country analysis for each respective country. The black line indicates the response; the grey areas indicate the 95% confidence interval.

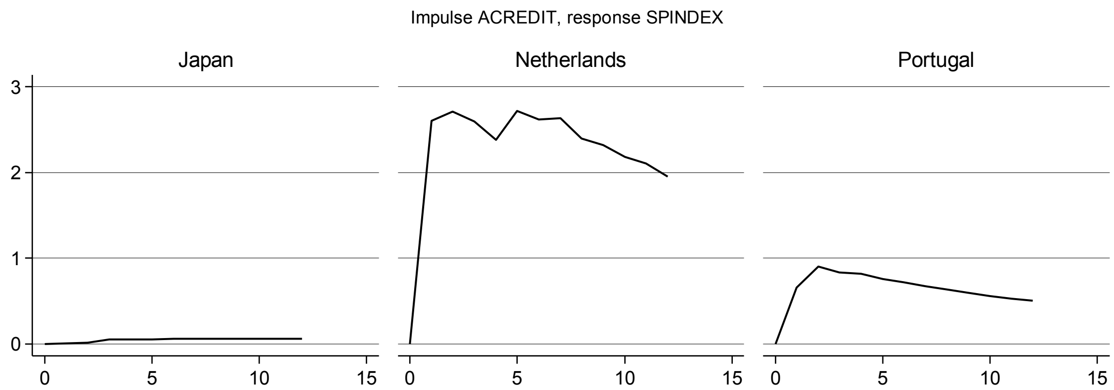


FIGURE 12 IRF VEC MODELS, RESPONSE ΔSPINDEX

Note: IRF indicates how the response variable reacts to a shock in the impulse variable, thereby suggesting a causal relationship. This model is based on the VEC results of the whole country analysis for each respective country. With an IRF after a VEC analysis it is not possible to display the 95% confidence interval.

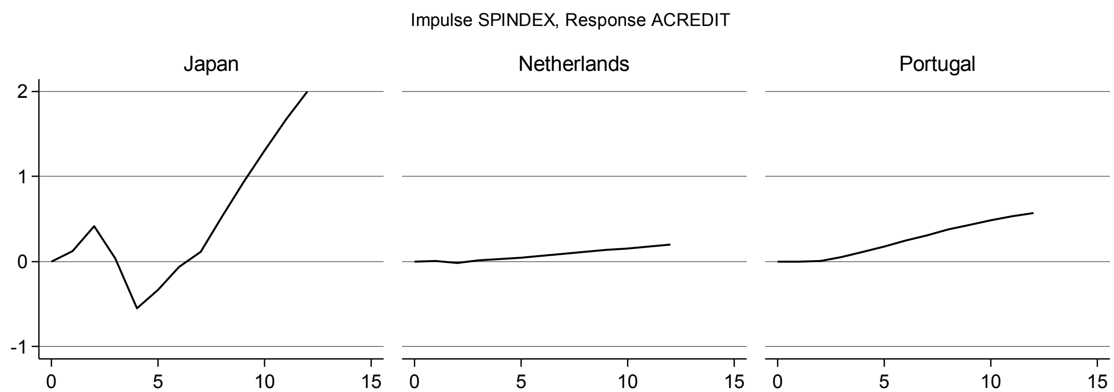


FIGURE 13 IRF VEC MODELS, RESPONSE ΔACREDIT

Note: IRF indicates how the response variable reacts to a shock in the impulse variable, thereby suggesting a causal relationship. This model is based on the VEC results of the whole country analysis for each respective country. With an IRF after a VEC analysis it is not possible to display the 95% confidence interval.

Malaysia

	SPB1		SPB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
main				
L.Y	0.128	0.136	0.150	0.191
L2.Y	0.006	-0.344**	0.054	-0.223*
L3.Y	0.146	0.125	0.116	0.135
L4.Y	-0.167	-0.311**	-0.101	-0.230*
L5.Y	-0.024	0.111	-0.046	0.079
L6.Y	-0.088	-0.124	-0.093	0.128
L.SPINDEX*SPB	-0.090	-0.073	-0.215	-0.006
L2.SPINDEX*SPB	-0.078	0.049	-0.317	0.024
L3.SPINDEX*SPB	0.045	-0.080	0.000	-0.078
L4.SPINDEX*SPB	-0.170	0.029	-0.510*	0.124*
L5.SPINDEX*SPB	-0.548**	-0.034	-0.199	-0.103
L6.SPINDEX*SPB	-0.040	0.010	0.117	0.057
L.ACREDIT*SPB	-0.308	0.288	0.519	0.350
L2.ACREDIT*SPB	0.958	0.027	-0.336	-0.481
L3.ACREDIT*SPB	0.286	-0.082	-2.406**	0.168
L4.ACREDIT*SPB	0.001	0.429	1.362	-0.446
L5.ACREDIT*SPB	-0.254	-0.249	-2.650**	0.150
L6.ACREDIT*SPB	-1.054	0.398	-1.717	-0.577*
L.ACREDIT*nonSPB	0.173		-0.083	
L2.ACREDIT*nonSPB	-0.237		0.163	
L3.ACREDIT*nonSPB	-0.310		-0.013	
L4.ACREDIT*nonSPB	0.423		0.379	
L5.ACREDIT*nonSPB	-0.521		-0.250	
L6.ACREDIT*nonSPB	-0.372		-0.445	
L.SPINDEX*nonSPB		-0.013		-0.064
L2.SPINDEX*nonSPB		0.087*		0.094**
L3.SPINDEX*nonSPB		0.035		0.011
L4.SPINDEX*nonSPB		0.058		0.042
L5.SPINDEX*nonSPB		-0.064		-0.090**
L6.SPINDEX*nonSPB		0.046		0.067*
_cons	13.500**	4.579**	10.417**	3.174*
Granger Tests:				
SP*SPB>AC		0.502		0.220
SP*nonSPB>AC		0.021		0.003
AC*SPB >SP	0.329		0.000	
AC*nonSPB >SP	0.417		0.672	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 35 VAR MALAYSIA: STOCK PRICE BUBBLES

Notes: 1. N: 99
2. Y corresponds to the respective dependent variable
3. The Granger test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. Lags are selected using the AIC selection criterion.
5. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
6. Spb1: stock price growth rate exceeds 15%. Spb2: deviation of 1 standard deviation from a smooth trend.

Malaysia

	TB1 ΔSPINDEX	ΔACREDIT	TB2 ΔSPINDEX	ΔACREDIT
main				
L.Y	0.189	0.145	0.065	0.155
L2.Y	-0.001	-0.285**	-0.035	-0.226*
L3.Y	0.070	0.160	0.098	0.130
L4.Y	-0.164	-0.179	-0.208*	-0.221*
L5.Y	-0.143	0.057	-0.206*	0.078
L6.Y	-0.120	-0.017	-0.156	0.113
L.SPINDEX*TB	-0.058	-0.118	-0.370	0.043
L2.SPINDEX*TB	-0.019	0.113	-0.090	-0.155
L3.SPINDEX*TB	0.351	0.020	1.391*	0.031
L4.SPINDEX*TB	-0.018	0.050	1.926	0.349
L5.SPINDEX*TB	-0.653*	-0.084	1.159	-0.400
L6.SPINDEX*TB	0.345	-0.019	-0.242	0.238
L.ACREDIT*TB	-0.445	0.405	2.307	1.205*
L2.ACREDIT*TB	1.185	-0.156	-0.059	-0.909
L3.ACREDIT*TB	-0.327	-0.167	-5.555**	-0.419
L4.ACREDIT*TB	-0.641	0.038	0.000	0.000
L5.ACREDIT*TB	1.592	-0.139	0.000	0.000
L6.ACREDIT*TB	-2.588**	0.344	0.353	-0.778
L.ACREDIT*nonTB	0.299		-0.184	
L2.ACREDIT*nonTB	-0.006		0.295	
L3.ACREDIT*nonTB	-0.119		-0.016	
L4.ACREDIT*nonTB	0.450		0.427	
L5.ACREDIT*nonTB	-0.717		-0.546	
L6.ACREDIT*nonTB	-0.318		-0.327	
L.SPINDEX*nonTB		-0.018		-0.044
L2.SPINDEX*nonTB		0.070*		0.073*
L3.SPINDEX*nonTB		0.000		-0.003
L4.SPINDEX*nonTB		0.053		0.046
L5.SPINDEX*nonTB		-0.068*		-0.068*
L6.SPINDEX*nonTB		0.050		0.043
_cons	7.598	3.340*	10.286*	3.021*
Granger Tests:				
SP*TB>AC		0.640		0.139
SP*nonTB>AC		0.090		0.037
AC*TB >SP	0.084		0.045	
AC*nonTB >SP	0.225		0.482	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 36 VAR MALAYSIA: TWIN BUBBLES

Notes: 1. N: 99
2. Y corresponds to the dependent variable
3. The Granger test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. Lags are selected using the AIC selection criterion.
5. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
6. Tb1: twin boom 1, which denotes that stock price boom and credit boom occur simultaneously.

Belgium

	SPB1 ΔSPINDEX	ΔACREDIT	SPB2 ΔSPINDEX	ΔACREDIT
main				
L.Y	0.037	0.103	0.136	0.067
L2.Y	0.099	0.110	0.010	0.147
L3.Y	0.086	0.205	0.212*	0.082
L4.Y	-0.154	0.327*	-0.001	0.372**
L5.Y	-0.119	-0.050	0.102	-0.112
L6.Y	-0.119	0.112	0.102	-0.268*
L7.Y	0.003	-0.365*	-0.009	-0.088
L8.Y	-0.161	-0.000	-0.091	0.033
L.SPINDEX*SPB	0.002	-0.005	-0.547***	0.010
L2.SPINDEX*SPB	0.137	0.030	0.398*	0.006
L3.SPINDEX*SPB	0.294	0.043**	0.391*	-0.020
L4.SPINDEX*SPB	0.158	0.059***	0.206	0.019
L5.SPINDEX*SPB	-0.093	0.027	-0.053	0.032
L6.SPINDEX*SPB	-0.044	0.038*	-0.155	0.016
L7.SPINDEX*SPB	-0.416	0.016	-0.260	0.021
L8.SPINDEX*SPB	-0.171	-0.007	-0.063	0.008
L.ACREDIT*SPB	-1.148	-0.225	-0.781	-0.089
L2.ACREDIT*SPB	-0.923	-0.208	-9.185**	0.546
L3.ACREDIT*SPB	-0.068	-0.451*	2.280	-0.186
L4.ACREDIT*SPB	4.022*	-0.127	-2.708	-0.228
L5.ACREDIT*SPB	6.867***	-0.092	8.220**	0.077
L6.ACREDIT*SPB	-1.220	-0.434*	-5.673	0.317
L7.ACREDIT*SPB	-4.808*	0.395	2.790	-0.263
L8.ACREDIT*SPB	-1.455	0.127	-1.383	0.552*
L.ACREDIT*nonSPB	-2.022		-0.610	
L2.ACREDIT*nonSPB	0.068		0.284	
L3.ACREDIT*nonSPB	1.505		-0.831	
L4.ACREDIT*nonSPB	1.159		2.147	
L5.ACREDIT*nonSPB	-1.362		1.362	
L6.ACREDIT*nonSPB	-1.529		-0.959	
L7.ACREDIT*nonSPB	-0.941		-1.291	
L8.ACREDIT*nonSPB	-1.627		-1.484	
L.SPINDEX*nonSPB		-0.005		-0.009
L2.SPINDEX*nonSPB		-0.001		-0.001
L3.SPINDEX*nonSPB		-0.007		0.006
L4.SPINDEX*nonSPB		0.007		0.020
L5.SPINDEX*nonSPB		0.006		0.011
L6.SPINDEX*nonSPB		-0.001		-0.004
L7.SPINDEX*nonSPB		0.014		0.023*
L8.SPINDEX*nonSPB		0.001		0.000
_cons	27.355**	1.877*	18.555*	3.208***
Granger Tests:				
SP*SPB>AC		0.002		0.527
SP*nonSPB>AC		0.774		0.080
AC*SPB >SP	0.016		0.000	
AC*nonSPB >SP	0.107		0.217	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 37 VAR BELGIUM: STOCK PRICE BUBBLES

Notes: 1. N: 137
2. Y corresponds to the dependent variable
3. The Granger test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
5. Spb1: stock price growth rate exceeds 15%. Spb2: deviation of 1 standard deviation from a smooth trend.

Belgium

	ACB1 ΔSPINDEX	ACB1 ΔACREDIT	ACB2 ΔSPINDEX	ACB2 ΔACREDIT
main				
L.Y	0.067	0.143	-0.050	0.085
L2.Y	0.214*	0.190*	0.278**	0.202*
L3.Y	0.270**	0.103	0.163	0.107
L4.Y	0.020	0.445***	-0.017	0.465***
L5.Y	0.084	-0.077	0.030	-0.013
L6.Y	0.078	-0.315*	0.022	-0.255
L7.Y	-0.104	-0.049	-0.127	-0.095
L8.Y	-0.143	0.138	-0.044	0.101
L.SPINDEX*ACB	-0.276	-0.015	0.530*	-0.016
L2.SPINDEX*ACB	-0.785	0.011	-0.793***	0.014
L3.SPINDEX*ACB	-0.450	-0.018	0.208	0.003
L4.SPINDEX*ACB	-0.497	-0.015	-0.373	-0.006
L5.SPINDEX*ACB	-0.105	0.017	-0.203	0.008
L6.SPINDEX*ACB	-0.032	-0.022	0.068	-0.009
L7.SPINDEX*ACB	0.147	0.048	-0.111	0.017
L8.SPINDEX*ACB	-0.057	-0.026	-0.459*	0.021
L.ACREDIT*ACB	0.786	-0.357	-0.276	0.099
L2.ACREDIT*ACB	-0.411	-0.162	-3.080	-0.189
L3.ACREDIT*ACB	1.281	-0.147	2.844	-0.000
L4.ACREDIT*ACB	-0.507	-0.241	-2.926	-0.157
L5.ACREDIT*ACB	3.711	0.066	0.007	-0.199
L6.ACREDIT*ACB	-1.061	0.320	0.682	0.151
L7.ACREDIT*ACB	-2.213	-0.050	-5.574*	0.218
L8.ACREDIT*ACB	-3.295	-0.509	-4.270	-0.004
L.ACREDIT*nonACB	-1.803		-1.012	
L2.ACREDIT*nonACB	-0.556		-0.700	
L3.ACREDIT*nonACB	-0.649		-1.339	
L4.ACREDIT*nonACB	1.396		0.959	
L5.ACREDIT*nonACB	1.364		1.894	
L6.ACREDIT*nonACB	-2.302		-2.475	
L7.ACREDIT*nonACB	-2.602		-1.353	
L8.ACREDIT*nonACB	-0.375		-0.114	
L.SPINDEX*nonACB		-0.014		-0.007
L2.SPINDEX*nonACB		0.000		-0.002
L3.SPINDEX*nonACB		-0.002		-0.002
L4.SPINDEX*nonACB		0.012		0.015
L5.SPINDEX*nonACB		0.009		0.007
L6.SPINDEX*nonACB		0.005		0.005
L7.SPINDEX*nonACB		0.022*		0.016
L8.SPINDEX*nonACB		-0.004		0.002
_cons	30.317**	2.824**	32.905**	2.350*
Granger Tests:				
SP*ACB>AC		0.888		0.763
SP*nonACB>AC		0.102		0.524
AC*ACB >SP	0.942		0.016	
AC*nonACB >SP	0.061		0.213	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 38 VAR BELGIUM: CREDIT BUBBLES

Notes: 1. N: 99
2. Y corresponds to the dependent variable
3. The Granger test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
5. Acb1: credit growth rate exceeds 15%. Acb2: deviation of 1.5 standard deviation from a smooth trend.

Finland

	SPB1		SPB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
main				
L.Y	0.054	0.270**	0.051	0.313***
L2.Y	0.152	-0.056	0.015	-0.039
L.SPINDEX*SPB	0.155	0.003	0.115	0.003
L2.SPINDEX*SPB	-0.227	0.002	-0.040	0.006*
L.ACREDIT*SPB	-0.523	0.319*	-0.598	0.061
L2.ACREDIT*SPB	-9.301	0.099	-19.814***	0.371*
L.ACREDIT*nonSPB	-5.575		-3.890	
L2.ACREDIT*nonSPB	-3.839		-1.677	
L.SPINDEX*nonSPB		-0.003		0.004
L2.SPINDEX*nonSPB		-0.003		-0.005
_cons	29.152*	1.320***	27.271*	1.535***
Granger Tests:				
SP*SPB>AC		0.371		0.050
SP*nonSPB>AC		0.586		0.377
AC*SPB >SP	0.063		0.000	
AC*nonSPB >SP	0.051		0.257	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 39 VAR FINLAND: STOCK PRICE BUBBLES

Notes: 1. N: 136
2. Y corresponds to the dependent variable
3. The Granger test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
5. Spb1: stock price growth rate exceeds 15%. Spb2: deviation of 1 standard deviation from a smooth trend.

Finland

	ACB1 ΔSPINDEX	ACB1 ΔACREDIT	ACB2 ΔSPINDEX	ACB2 ΔACREDIT
main				
L.Y	0.199*	0.383***	0.437***	0.424***
L2.Y	-0.094	0.010	-0.382***	0.053
L.SPINDEX*ACB	-0.231	-0.002	-0.799***	-0.012*
L2.SPINDEX*ACB	1.123***	0.010	0.897***	-0.001
L.ACREDIT*ACB	-16.670	-0.212	-12.318*	-0.492**
L2.ACREDIT*ACB	2.318	0.133	-4.000	-0.173
L.ACREDIT*nonACB	-4.618		-4.666	
L2.ACREDIT*nonACB	-3.974		-0.556	
L.SPINDEX*nonACB		0.003		0.005
L2.SPINDEX*nonACB		0.001		-0.002
_cons	30.028*	1.551***	23.331*	1.509***
Granger Tests:				
SP*ACB>AC		0.511		0.080
SP*nonACB>AC		0.457		0.311
AC*ACB >SP	0.158		0.030	
AC*nonACB >SP	0.025		0.177	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 40 VAR FINLAND: CREDIT BUBBLES

Notes: 1. N: 136
2. Y corresponds to the dependent variable
3. The Granger test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
5. Acb1: credit growth rate exceeds 15%. Acb2: deviation of 1.5 standard deviation from a smooth trend.

Finland

	TB1		TB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
main				
L.Y	0.198*	0.373***	0.469***	0.381***
L2.Y	-0.054	-0.000	-0.425***	0.001
L.SPINDEX*TB	9.623	-0.066	0.277	-0.011
L2.SPINDEX*TB	-2.925	-0.001	2.159***	-0.007
L.ACREDIT*TB	-42.909**	0.098	45.826	-0.776
L2.ACREDIT*TB	4.993	0.191	26.863	-0.194
L.ACREDIT*nonTB	-5.854*		-7.930**	
L2.ACREDIT*nonTB	-2.514		1.529	
L.SPINDEX*nonTB		0.002		0.002
L2.SPINDEX*nonTB		0.003		0.003
_cons	28.506*	1.528***	23.309*	1.549***
Granger Tests:				
SP*TB>AC		0.939		0.815
SP*nonTB>AC		0.339		0.427
AC*TB >SP	0.028		0.244	
AC*nonTB >SP	0.026		0.007	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 41 VAR FINLAND: TWIN BUBBLES

Notes: 1. N: 136
2. Y corresponds to the dependent variable
3. The Granger test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
5. Tb1: twin boom 1, which denotes that stock price boom and credit boom occur simultaneously.

France

	SPB1		SPB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
main				
L.Y	0.260*	0.460***	0.203*	0.399***
L2.Y	0.011	0.175	0.012	0.235**
L.SPINDEX*SPB	0.014	0.047	0.160	0.071
L2.SPINDEX*SPB	-0.046	-0.014	0.376	0.000
L.ACREDIT*SPB	-0.560	-0.121	-1.306	-0.149
L2.ACREDIT*SPB	-0.128	0.201*	-1.048	0.254
L.ACREDIT*nonSPB	-0.101		-0.161	
L2.ACREDIT*nonSPB	-0.986		-0.345	
L.SPINDEX*nonSPB		-0.016		-0.001
L2.SPINDEX*nonSPB		0.012		0.002
_cons	31.358*	7.791***	26.844	8.387***
Granger Tests:				
SP*SPB>AC		0.130		0.114
SP*nonSPB>AC		0.565		0.986
AC*SPB >SP	0.611		0.002	
AC*nonSPB >SP	0.080		0.600	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 42 VAR FRANCE: STOCK PRICE BUBBLES

Notes: 1. N: 143
2. Y corresponds to the dependent variable
3. The Granger test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
5. Spb1: stock price growth rate exceeds 15%. Spb2: deviation of 1 standard deviation from a smooth trend.

France

	ACB1		ACB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
main				
L.Y			0.187*	0.390***
L2.Y			0.024	0.329***
L.ACREDIT*ACB			-1.888	-0.481**
L2.ACREDIT*ACB			-3.137**	-0.252
L.ACREDIT*nonACB			-0.513	
L2.ACREDIT*nonACB			-0.316	
L.SPINDEX*nonACB				-0.008
L2.SPINDEX*nonACB				0.001
L.SPINDEX*ACB			0.108	-0.040
L2.SPINDEX*ACB			-0.693*	-0.014
_cons			36.440**	8.894***
Granger Tests:				
SP*ACB>AC		.		0.739
SP*nonACB>AC		.		0.827
AC*ACB >SP	.		0.008	
AC*nonACB >SP	.		0.201	

* p<0.05, ** p<0.01, *** p<0.001

Table 43 VAR France: Credit bubbles

Notes: 1. N: 136
2. Y corresponds to the dependent variable
3. The Granger test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
5. Acb1: omitted because of too few credit bubble observations. Acb2: deviation of 1.5 standard deviation from a smooth trend.

Germany

	SPB1		SPB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
main				
L.Y	0.337**	0.139	0.266**	0.096
L2.Y	-0.094	0.280**	-0.178*	0.185*
L3.Y	0.248	0.053	0.099	0.004
L4.Y	-0.067	0.325**	-0.016	0.461***
L5.Y	0.123	0.115	0.029	-0.018
L.SPINDEX*SPB	-0.266	0.031	0.070	-0.025
L2.SPINDEX*SPB	0.080	0.037	0.342	0.034
L3.SPINDEX*SPB	-0.296	0.038	0.068	0.196**
L4.SPINDEX*SPB	0.076	0.009	0.260	0.040
L5.SPINDEX*SPB	-0.300	0.092*	0.104	0.107
L.ACREDIT*SPB	-0.326	-0.113	-2.646***	-0.073
L2.ACREDIT*SPB	0.374	-0.276*	0.651	-0.548*
L3.ACREDIT*SPB	-0.016	-0.077	0.007	-0.026
L4.ACREDIT*SPB	-0.909***	0.184	-1.428*	0.250
L5.ACREDIT*SPB	0.837**	-0.130	0.643	0.168
L.ACREDIT*nonSPB	-0.634		-0.072	
L2.ACREDIT*nonSPB	0.157		0.054	
L3.ACREDIT*nonSPB	0.650*		0.527*	
L4.ACREDIT*nonSPB	-0.482		-0.739***	
L5.ACREDIT*nonSPB	0.040		0.591*	
L.SPINDEX*nonSPB		0.066		0.022
L2.SPINDEX*nonSPB		-0.010		0.025
L3.SPINDEX*nonSPB		-0.002		-0.032
L4.SPINDEX*nonSPB		0.098*		0.060
L5.SPINDEX*nonSPB		0.015		0.027
_cons	15.437	3.355	5.789	4.317
Granger Tests:				
SP*SPB>AC		0.237		0.076
SP*nonSPB>AC		0.075		0.253
AC*SPB >SP	0.002		0.000	
AC*nonSPB >SP	0.108		0.001	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 44 VAR GERMANY: STOCK PRICE BUBBLES

Notes: 1. N: 140
2. Y corresponds to the dependent variable
3. The Granger test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
5. Spb1: stock price growth rate exceeds 15%. Spb2: deviation of 1 standard deviation from a smooth trend.

Germany

	ACB1		ACB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
main				
L.Y			0.212*	0.120
L2.Y			0.008	0.182*
L3.Y			0.027	-0.025
L4.Y			-0.004	0.413***
L5.Y			-0.050	0.073
L.ACREDIT*nonACB			-0.377	
L2.ACREDIT*nonACB			0.455	
L3.ACREDIT*nonACB			0.300	
L4.ACREDIT*nonACB			-0.985***	
L5.ACREDIT*nonACB			0.508	
L.SPINDEX*nonACB				0.056*
L2.SPINDEX*nonACB				-0.019
L3.SPINDEX*nonACB				0.006
L4.SPINDEX*nonACB				0.035
L5.SPINDEX*nonACB				0.044
L.SPINDEX*ACB			1.285	-0.031
L2.SPINDEX*ACB			0.334	-0.865
L3.SPINDEX*ACB			-2.128	-0.192
L4.SPINDEX*ACB			0.871	0.748
L5.SPINDEX*ACB			0.831	-1.522*
L.ACREDIT*ACB			-0.963	-0.210
L2.ACREDIT*ACB			0.135	0.253
L3.ACREDIT*ACB			1.221	0.172
L4.ACREDIT*ACB			-0.731	-0.016
L5.ACREDIT*ACB			-0.319	0.214
_cons			6.425	3.972
Granger Tests:				
SP*ACB>AC		.		0.015
SP*nonACB>AC		.		0.072
AC*ACB >SP	.		0.718	
AC*nonACB >SP	.		0.002	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 45 VAR GERMANY: CREDIT BUBBLES

Notes: 1. N: 140
2. Y corresponds to the dependent variable
3. The Granger test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
5. Acb1: omitted because of too few credit bubble observations. Acb2: deviation of 1.5 standard deviation from a smooth trend.

Japan

	SPB1		SPB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
main				
ECM	0.003	-0.003	0.091**	-0.006
LD.Y	0.251*	0.079	0.198	0.111
L2D.Y	-0.061	-0.029	-0.088	-0.062
L3D.Y	0.117	0.214*	0.016	0.234**
L4D.Y	-0.071	-0.030	-0.131	-0.018
LD.SPINDEX*SPB	0.019	-0.526	0.088	0.100
L2D.SPINDEX*SPB	0.014	-0.200	0.166**	0.434
L3D.SPINDEX*SPB	0.050	-0.620	0.091	-0.208
L4D.SPINDEX*SPB	0.053	-0.809	0.073	-0.553
LD.ACREDIT*SPB	0.006	0.063*	-0.005	-0.017
L2D.ACREDIT*SPB	0.006	0.016	-0.020	-0.015
L3D.ACREDIT*SPB	0.034	-0.021	0.023	-0.025
L4D.ACREDIT*SPB	-0.024	-0.009	-0.028	0.015
LD.ACREDIT*nonSPB	0.007		0.005	
L2D.ACREDIT*nonSPB	0.004		0.004	
L3D.ACREDIT*nonSPB	0.043*		0.033	
L4D.ACREDIT*nonSPB	-0.020		-0.025	
LD.SPINDEX*nonSPB		0.031		0.112
L2D.SPINDEX*nonSPB		0.083		0.457
L3D.SPINDEX*nonSPB		-0.616		-0.128
L4D.SPINDEX*nonSPB		-0.893		-0.499
_cons	1.552	35.383	9.492	36.161
Granger Tests:				
SP*SPB>AC		0.535		0.623
SP*nonSPB>AC		0.377		0.724
AC*SPB>SP	0.350		0.300	
AC*nonSPB>SP	0.193		0.295	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 46 VEC JAPAN STOCK PRICE BUBBLES

Notes: 1. N: 146
2. Y corresponds to the dependent variable
3. The F test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. Lags are selected using the AIC selection criterion.
5. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
6. Spb1: stock price growth rate exceeds 15%. Spb2: deviation of 1 standard deviation from a smooth trend.

Japan

	ACB1 ΔSPINDEX	ΔACREDIT	ACB2 ΔSPINDEX	ΔACREDIT
main				
ECM	-0.021	-0.007	-0.009	0.028*
LD.Y	0.219*	0.116	0.222*	0.140
L2D.Y	-0.079	-0.045	-0.031	0.051
L3D.Y	0.127	0.313**	0.119	0.271*
L4D.Y	-0.069	-0.097	-0.031	0.095
LD.SPINDEX*ACB	-0.069	0.359	0.140	1.184
L2D.SPINDEX*ACB	0.004	0.603	0.145	0.619
L3D.SPINDEX*ACB	-0.020	-0.480	0.027	-0.545
L4D.SPINDEX*ACB	0.080	-0.690	0.008	-0.206
LD.ACREDIT*ACB	0.016	-0.040	0.012	-0.096
L2D.ACREDIT*ACB	0.006	-0.039	0.004	-0.031
L3D.ACREDIT*ACB	0.045*	-0.052	0.031	0.003
L4D.ACREDIT*ACB	-0.006	0.016	-0.019	-0.003
LD.ACREDIT*nonACB	0.002		0.027	
L2D.ACREDIT*nonACB	0.001		0.019	
L3D.ACREDIT*nonACB	0.038		0.033	
L4D.ACREDIT*nonACB	-0.000		-0.022	
LD.SPINDEX*nonACB		0.025		-0.184
L2D.SPINDEX*nonACB		0.340		0.365
L3D.SPINDEX*nonACB		-0.503		-0.413
L4D.SPINDEX*nonACB		-0.590		-0.104
_cons	1.988	33.795	1.298	32.996
Granger Tests:				
SP*ACB>AC		0.275		0.502
SP*nonACB>AC		0.358		0.808
AC>SP*ACB	0.332		0.659	
AC>SP*nonACB	0.521		0.305	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 47 VEC JAPAN CREDIT BUBBLES

Notes: 1. N: 146
2. Y corresponds to the dependent variable
3. The F test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. Lags are selected using the AIC selection criterion.
5. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
6. Acb1: credit growth rate exceeds 15%. Acb2: deviation of 1.5 standard deviation from a smooth trend.

Japan

	TB1		TB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
main				
ECM	-0.028*	-0.031*		
LD.Y	0.258**	0.048		
L2D.Y	-0.049	-0.108		
L3D.Y	0.182*	0.201*		
L4D.Y	-0.029	-0.079		
LD.SPINDEX*TB	-0.114	0.001		
L2D.SPINDEX*TB	0.032	-0.133		
L3D.SPINDEX*TB	0.082	-0.188		
L4D.SPINDEX*TB	0.099	-0.629		
LD.ACREDIT*TB	0.032	-0.008		
L2D.ACREDIT*TB	0.011	-0.007		
L3D.ACREDIT*TB	0.044*	-0.083		
L4D.ACREDIT*TB	-0.011	-0.033		
LD.ACREDIT*nonTB	0.016			
L2D.ACREDIT*nonTB	0.008			
L3D.ACREDIT*nonTB	0.049**			
L4D.ACREDIT*nonTB	-0.005			
LD.SPINDEX*nonTB		-0.100		
L2D.SPINDEX*nonTB		-0.244		
L3D.SPINDEX*nonTB		-0.467		
L4D.SPINDEX*nonTB		-0.725		
_cons	2.804	32.888	0.000	0.000
Granger Tests:				
SP*TB>AC		0.811		.
SP*nonTB>AC		0.307		.
AC>SP*TB	0.169		.	
AC>SP*nonTB	0.111		.	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 48 VEC JAPAN TWIN BUBBLES

Notes: 1. N: 146
2. Y corresponds to the dependent variable
3. The F test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. Lags are selected using the AIC selection criterion.
5. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
6. Results TB2 are omitted because there are too few observations with twin bubbles.
7. Tb1: twin boom 1, which denotes that stock price boom and credit boom occur simultaneously. Tb1 = spb1 * acb1, tb2 = spb2 * acb2.

Portugal

	ACB1 ΔSPINDEX	ΔACREDIT	ACB2 ΔSPINDEX	ΔACREDIT
ECM	-0.056	-0.010*	-0.112*	-0.006
LD.Y	0.270*	0.150	0.291**	0.174
L2D.Y	0.131	0.360***	0.143	0.467***
L3D.Y	0.148	0.022	0.109	-0.045
LD.SPINDEX*ACB	-0.095	-0.038	0.231	-0.041
L2D.SPINDEX*ACB	-0.198	-0.026	0.191	-0.015
L3D.SPINDEX*ACB	-0.316*	0.012	-0.087	-0.001
LD.ACREDIT*ACB	0.668	0.003	0.826	0.008
L2D.ACREDIT*ACB	0.202	0.031	0.220	-0.021
L3D.ACREDIT*ACB	0.092	0.051	-0.631	0.015
LD.ACREDIT*nonACB	0.410		1.011*	
L2D.ACREDIT*nonACB	-0.053		0.458	
L3D.ACREDIT*nonACB	-0.317		-0.630	
LD.SPINDEX*nonACB		-0.043		-0.031
L2D.SPINDEX*nonACB		-0.007		-0.007
L3D.SPINDEX*nonACB		0.046		0.036
_cons	-0.023	1.335*	-2.205	1.142*
F Tests:				
SP*ACB>AC		0.526		0.956
SP*nonACB>AC		0.231		0.356
AC*ACB >SP	0.359		0.253	
AC*nonACB >SP	0.657		0.127	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 49 ENGLE-GRANGER ERROR CORRECTION MODEL PORTUGAL CREDIT BUBBLES

Notes: 1. N: 146
2. Y corresponds to the dependent variable
3. The F test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. Lags are selected using the AIC selection criterion.
5. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
6. Acb1: credit growth rate exceeds 15%. Acb2: deviation of 1.5 standard deviation from a smooth trend.

Portugal

	TB1		TB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
ECM	-0.066	-0.008*		
LD.Y	0.234*	0.161		
L2D.Y	0.115	0.359***		
L3D.Y	0.070	0.021		
LD.SPINDEX*TB	0.058	-0.043		
L2D.SPINDEX*TB	-0.203	-0.014		
L3D.SPINDEX*TB	-0.223	0.032		
LD.ACREDIT*TB	0.495	0.013		
L2D.ACREDIT*TB	0.312	0.014		
L3D.ACREDIT*TB	0.028	0.013		
LD.ACREDIT*nonTB	0.515			
L2D.ACREDIT*nonTB	-0.010			
L3D.ACREDIT*nonTB	-0.292			
LD.SPINDEX*nonTB		-0.035		
L2D.SPINDEX*nonTB		-0.008		
L3D.SPINDEX*nonTB		0.039		
_cons	-0.509	1.304*		
F Tests:				
SP*TB>AC		0.493		
SP*nonTB>AC		0.313		
AC*TB >SP	0.648			
AC*nonTB>SP	0.589			

* p<0.05, ** p<0.01, *** p<0.001

TABLE 50 ENGLE-GRANGER ERROR CORRECTION MODEL PORTUGAL TWIN BUBBLES

Notes: 1. N: 146
2. Y corresponds to the dependent variable
3. The F test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. Lags are selected using the AIC selection criterion.
5. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
6. Results TB2 are omitted because there are too few observations with twin bubbles.
7. Tb1: twin boom 1, which denotes that stock price boom and credit boom occur simultaneously. Tb1 = spb1 * acb1, tb2 = spb2 * acb2.

Netherlands

	SPB1		SPB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
ECM	-0.127*	-0.005	0.062	-0.008*
LD.Y	-0.016	0.257**	0.155	0.284**
L2D.Y	0.041	0.164	0.145	0.178
L3D.Y	0.363***	-0.049	0.132	-0.061
L4D.Y	-0.025	0.252**	-0.218	0.216*
LD.SPINDEX*SPB	0.044	-0.000	-0.109	0.014
L2D.SPINDEX*SPB	0.002	-0.020	-0.057	-0.019
L3D.SPINDEX*SPB	-0.089	0.041**	0.150*	0.025
L4D.SPINDEX*SPB	-0.055	0.014	0.149*	0.015
LD.ACREDIT*SPB	2.879***	-0.001	1.568*	-0.006
L2D.ACREDIT*SPB	-0.776	-0.016*	-1.165	-0.024*
L3D.ACREDIT*SPB	-0.830	-0.016*	-0.493	-0.007
L4D.ACREDIT*SPB	-0.594	-0.004	-1.233	-0.010
LD.ACREDIT*nonSPB	2.903***		1.468*	
L2D.ACREDIT*nonSPB	-0.788		-1.213	
L3D.ACREDIT*nonSPB	-0.906		-0.354	
L4D.ACREDIT*nonSPB	-0.651		-1.097	
LD.SPINDEX*nonSPB		-0.003		0.014
L2D.SPINDEX*nonSPB		-0.035*		-0.040*
L3D.SPINDEX*nonSPB		0.026		0.018
L4D.SPINDEX*nonSPB		0.015		0.009
_cons	0.026	3.889**	19.063	3.943*
F Tests:				
SP*SPB>AC		0.015		0.130
SP*nonSPB>AC		0.030		0.103
AC*SPB>SP	0.000		0.007	
AC*nonSPB>SP	0.000		0.014	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 51 ENGLE-GRANGER ERROR CORRECTION MODEL NETHERLANDS STOCK PRICE BUBBLES

Notes: 1. N: 146
2. Y corresponds to the dependent variable
3. The F test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. Lags are selected using the AIC selection criterion.
5. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
6. Spb1: stock price growth rate exceeds 15%. Spb2: deviation of 1 standard deviation from a smooth trend.

Netherlands

	ACB1		ACB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
ECM	-0.097*	-0.005	-0.050	-0.007*
LD.Y	0.123	0.308***	0.183	0.328***
L2D.Y	0.036	0.145	0.112	0.185
L3D.Y	0.349***	-0.067	0.277**	-0.141
L4D.Y	0.052	0.207*	0.036	0.207*
LD.SPINDEX*ACB	3.355**	0.037	0.150	-0.002
L2D.SPINDEX*ACB	0.074	0.237*	-0.037	0.015
L3D.SPINDEX*ACB	2.806**	0.298*	0.147	0.003
L4D.SPINDEX*ACB	-1.515	0.128	0.103	-0.016
LD.ACREDIT*ACB	-2.726	-0.076	2.064**	-0.015
L2D.ACREDIT*ACB	-0.521	-0.409*	-0.781	-0.062*
L3D.ACREDIT*ACB	-4.115**	-0.407	-1.049	0.016
L4D.ACREDIT*ACB	1.163	-0.167	-0.512	0.027
LD.ACREDIT*nonACB	2.364***		2.347***	
L2D.ACREDIT*nonACB	-0.560		-0.649	
L3D.ACREDIT*nonACB	0.109		-0.855	
L4D.ACREDIT*nonACB	-0.977		-0.313	
LD.SPINDEX*nonACB		-0.011		-0.012
L2D.SPINDEX*nonACB		-0.041**		-0.033*
L3D.SPINDEX*nonACB		0.020		0.019
L4D.SPINDEX*nonACB		0.011		0.001
_cons	-5.336	4.344**	-1.920	4.511**
F Tests:				
SP*ACB>AC		0.040		0.922
SP*nonACB>AC		0.010		0.076
AC*ACB >SP	0.065		0.008	
AC*nonACB >SP	0.002		0.006	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 52 ENGLE-GRANGER ERROR CORRECTION MODEL NETHERLANDS CREDIT BUBBLES

Notes: 1. N: 146
2. Y corresponds to the dependent variable
3. The F test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. Lags are selected using the AIC selection criterion.
5. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
6. Acb1: credit growth rate exceeds 15%. Acb2: deviation of 1.5 standard deviation from a smooth trend.

Netherlands

	TB1		TB2	
	ΔSPINDEX	ΔACREDIT	ΔSPINDEX	ΔACREDIT
ECM	-0.079*	-0.005	-0.053	-0.007
LD.Y	0.078	0.310***	0.204*	0.301***
L2D.Y	0.026	0.143	0.082	0.172
L3D.Y	0.312***	-0.094	0.221*	-0.080
L4D.Y	0.001	0.236**	0.026	0.178*
LD.SPINDEX*TB	1.580	-0.822*	1.244***	0.058
L2D.SPINDEX*TB	-0.360	-0.034*	-0.087	0.056
L3D.SPINDEX*TB	0.417	-0.042	-0.008	-0.020
L4D.SPINDEX*TB	1.304	-0.483*	0.692	0.006
LD.ACREDIT*TB	-0.188	1.227*	0.419	-0.114
L2D.ACREDIT*TB	0.000	0.000	-0.675	-0.119
L3D.ACREDIT*TB	-0.697	0.125	-0.379	0.059
L4D.ACREDIT*TB	-2.612	0.797*	-1.786*	0.015
LD.ACREDIT*nonTB	2.168***		2.342***	
L2D.ACREDIT*nonTB	-0.713		-0.687	
L3D.ACREDIT*nonTB	-0.154		-0.603	
L4D.ACREDIT*nonTB	-0.671		-0.786	
LD.SPINDEX*nonTB		-0.016		-0.014
L2D.SPINDEX*nonTB		-0.037**		-0.035**
L3D.SPINDEX*nonTB		0.016		0.018
L4D.SPINDEX*nonTB		0.012		0.007
_cons	-1.047	4.361**	1.518	4.603**
F Tests:				
SP*TB>AC		0.028		0.346
SP*nonTB>AC		0.019		0.037
AC*TB >SP	0.585		0.084	
AC*nonTB>SP	0.009		0.001	

* p<0.05, ** p<0.01, *** p<0.001

TABLE 53 ENGLE-GRANGER ERROR CORRECTION MODEL NETHERLANDS CREDIT BUBBLES

Notes: 1. N: 146
2. Y corresponds to the dependent variable
3. The F test SP>AC (AC>SP) examines the null hypothesis that the lagged coefficients of SPINDEX (ACREDIT) do not Granger cause ACREDIT (SPINDEX) for both bubble and non-bubble observations. The coefficients indicate the kind of relationship.
4. Lags are selected using the AIC selection criterion.
5. SPINDEX*non-bubble is dropped because of perfect collinearity with SPINDEX. Similarly, ACREDIT*non-bubble is perfectly collinear with ACREDIT.
6. Tb1: twin boom 1, which denotes that stock price boom and credit boom occur simultaneously. Tb1 = spb1 * acb1, tb2 = spb2 * acb2.