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BUBBLE DETECTION AND CONTAGION: AN ANALYSIS BY SEGMENTS OF THE U.S. STOCK, REAL ESTATE, AND CREDIT MARKETS

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To Daniela, for her love.

"Para ser grande, sê inteiro." (Ricardo Reis)

Abstract

Excessive credit growth and asset price bubbles are among the origins of several banking crises. The recent global financial crisis is a remarkable example of how exuberance in financial markets can cause severe costs to economic activity. Therefore, it is of utmost importance to inspect whether bubbles in a specific market may transmit to other markets and threaten financial stability.

The present work proposes to detect bubbles and their contagion effects between the U.S. stock, real estate, and credit markets over 1980-2019. Particularly, the stock market is divided into non-financial and bank stocks; the real estate market is split into residential and commercial properties; and finally, the credit market is segmented into credit to households and credit to non-financial corporations. The segmented analysis of each market sheds light on the mechanisms through which bubbles spread across markets. Therefore, the methodology proposed by Phillips, Shi, and Yu (2015) is applied to detect and date-stamp bubble periods. Furthermore, the present study tests for bubble contagion with the method proposed by Greenaway-McGrevy and Phillips (2016), which estimates the sensitivity of a market to exuberance in another.

The main findings indicate that the housing market, credit to households, and credit to non-financial corporations experienced more quarters in which bubbles were detected than the others, though bubbles in the latter last for shorter periods. The results of the contagion analysis provide evidence of bubble contagion from the housing market to all the others. Additionally, housing bubbles may transmit to the stock market through the credit market, which points to this market being a fundamental driver of bubble contagion. Finally, there are two current ongoing bubbles in which contagion is found. The results highlight the need to develop macroprudential policies to prevent the emergence of multiple bubbles that could damage the financial system.

JEL codes: G01; G12; G21; R31

Keywords: Financial Bubbles; Bubble Contagion; Stock Market; Real Estate Market; Credit Market

Resumo

O crescimento excessivo do crédito e bolhas nos preços dos ativos estão na base da maioria das crises bancárias. A recente crise financeira global é um exemplo notório de como exuberância nos mercados financeiros podem causar graves perdas para a atividade económica. Assim, é de grande importância investigar se bolhas num determinado mercado se podem transmitir para outros mercados e ameaçar a estabilidade financeira.

Neste sentido, esta dissertação procura detetar bolhas e os seus efeitos de contágio entre os mercados acionista, imobiliário e do crédito nos Estados Unidos entre 1980 e 2019. Particularmente, o mercado acionista é dividido em empresas não financeiras e bancos; o imobiliário em propriedades residenciais e comerciais; e, finalmente, o do crédito em crédito às famílias e crédito às empresas não financeiras. Esta análise segmentada contribui, assim, para a explicação dos mecanismos através dos quais uma determinada bolha pode contagiar outros mercados. Para tal, é usada a metodologia proposta por Phillips, Shi e Yu (2015), que permite identificar períodos de bolhas e, para testar a presença de contágio, é utilizada a proposta de Greenaway-Mcgrevy e Phillips (2016), que permite estimar a sensibilidade de um mercado à exuberância noutro.

As principais conclusões indicam que foram detetadas bolhas em bastante mais trimestres nos mercados residencial e do crédito, embora no crédito às empresas não financeiras estas têm uma menor duração. Relativamente ao contágio, os resultados comprovam a existência de transmissão de bolhas do mercado residencial para todos os outros mercados em análise. Ademais, estas transmitem-se para o mercado acionista, sobretudo, através do crédito, o que evidencia o seu papel fundamental como transmissor de bolhas. Adicionalmente, existem atualmente duas bolhas financeiras em curso. Assim, os resultados enfatizam a necessidade de desenvolver políticas macroprudenciais para prevenir o aparecimento de múltiplas bolhas que podem fazer colapsar o sistema financeiro.

Códigos JEL: G01; G12; G21; R31

Palavras-chave: Bolhas Financeiras; Contágio de Bolhas; Mercado Acionista; Mercado Imobiliário; Mercado do Crédito

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1 Introduction

The recent global financial crisis has highlighted the importance of being alert to the build-up of vulnerabilities in the financial markets by capturing warning signals that allow policymakers to prevent a financial collapse. Therefore, several institutions worldwide are interested in monitoring the evolution of variables that can predict a forthcoming turmoil to react in due time and mitigate the devastating impacts of a financial crisis.

In this respect, many authors have concluded that excessive credit growth and asset price bubbles are the main causes of banking crises (Alessi & Detken, 2018; Anundsen, Gerdrup, Hansen, & Kragh-Sørensen, 2016; Kauko, 2014; Virtanen, Tölö, Virén, & Taipalus, 2018). Thus, policymakers should monitor asset price bubbles fuelled by loan growth, often called "leveraged bubbles" (Jordà, Schularick, & Taylor, 2015), and so they should be worried about whether an explosive behaviour would be symptomatic of future imbalances.

In this context, it is of utmost importance to inspect whether bubbles in a specific market may transmit to other assets and create a harmful environment in the financial system. This is particularly relevant since the literature identified several mechanisms through which financial markets are interconnected, both in a cross-asset perspective and in a cross-border sense, as will be clarified in the literature review (chapter 2). Also, historical episodes of explosiveness encourage to explore the emergence of multiple bubbles in financial markets, and, in particular, stock, real estate, and credit markets as they experience bubble periods recurrently, as will be addressed in the following chapter. For instance, the recent global financial crisis has strengthened the relevance of understanding how housing exuberance and credit booms may reinforce each other and precipitate the collapse of the financial system.

The above-mentioned framework motivates the analysis of the present work. As asset price bubbles and credit booms increase the likelihood of financial crises, the present work proposes to detect bubbles and their contagion effects among the U.S. stock, real estate, and credit markets. In particular, an analysis of segments of each market is proposed to shed light on the transmission effects across them. More precisely, the present work inspects through which segments bubbles spread between the three markets referred to above. To this end, the stock market is divided into non-financial and bank stocks; the real estate market is split into residential and commercial properties; and finally, the credit market is segmented into credit to households and non-profit institutions serving households (hereafter referred to just as credit to households) and credit to non-financial corporations. The analysis of bubble detection and contagion in these markets taking different segments allows for a deeper understanding of what underlies their behaviour as well as the contagion between them.

In this manner, the present work proposes to answer two main questions. First, do some segments of the stock, real estate, and credit markets experience more bubbles than others? Second, do bubbles transmit between them? This analysis contributes to understand bubble behaviour of key markets and bubble contagion between them (all at the level of segments). And the importance of this knowledge directly derives from the importance of these markets for financial stability.

In the present work, data refer to U.S. markets for three reasons. First, testing for bubble detection and contagion in different countries may induce wrong conclusions. The financial system of each country has its own characteristics, hence, to present robust results one should select countries with similar features and consider control variables to avoid these biases (Hackethal, 2000). Data availability is so a constraint. Second, U.S. financial markets play a central role in global markets (e.g. Ehrmann, Fratzscher, & Rigobon, 2011). Therefore, U.S. markets are deemed sufficiently representative for analysing bubble contagion effects, as the U.S. has one of the most developed financial systems. Third, the recent experience evidences the importance of monitoring asset price bubbles that emerge in U.S. markets as it sowed the seeds of the Great Recession.

To address the questions above, the present work applies the methodology proposed by Phillips et al. (2015) (hereafter referred to as PSY) that allows detecting and date-stamping bubble periods. More specifically, this methodology proposes right-tailed unit root tests to search for explosive behaviour in the price-to-fundamentals ratio as evidence of a speculative bubble. These tests are applied to the valuation measure of each market using quarterly data over 1980-2019. This procedure allows us to identify bubble episodes and infer which markets face more bubble periods. Furthermore, the present work tests for bubble contagion to evaluate if bubbles spread across markets by applying the method proposed by Greenaway-McGrevy and Phillips (2016).

Although mostly following the Great Recession an extensive research literature on financial bubbles and their implications for financial stability has emerged, the main contribution of the present dissertation is threefold. First, the present work checks for bubble contagion in and between three different markets: stock, real estate, and credit. To the best of my knowledge, no one has explored the contagion of explosive movements between these markets taken together in the same work. Although recent literature is plenty of evidence of interconnectedness between these markets, bubble contagion is still a subject little explored. The results indicate that housing bubbles are more contagious to the commercial segment and the credit to households, but also evidence of bubble contagion to the stock market and credit to non-financial corporations was found, which is particularly significant during the build-up phase of the Great Recession. Furthermore, the results suggest that housing bubbles may transmit to the stock market through the credit market, which is consistent with the view that the credit market is a fundamental driver of bubble contagion between these markets. Besides, bank stocks depend to a great extent on the performance of the remainder of the stock market and not so on the residential property prices. Second, to the best of my knowledge, there is not any other relevant work that proposed to detect bubbles considering this segmented analysis for all these crucial markets. The results highlight the relevance of this disaggregation as some segments experience more bubble periods than others. Particularly, the credit to non-financial corporations is the market where more bubbles were detected. The residential property market experienced the sharpest bubble. Conversely, bubbles in the stock market are less frequent and of lesser duration, in line with the results of Gómez-González, Ojeda-Joya, Franco, and Torres (2017). Third, the segmented analysis made possible to find out that the housing market and the credit to non-financial corporations are currently undergoing a bubble period and, moreover, evidence of bi-directional bubble contagion is found between these markets during these current ongoing bubbles. As the results showed that these markets may transmit exuberance to other markets, policymakers should be alert.

In sum, the present work contributes to the literature on empirical detection of bubbles in the stock, real estate, and credit markets, and sheds light on the linkages between these markets by analysing bubble contagion between segments of each market.

The present work is organized as follows. The following chapter presents a literature review on historical bubble episodes and how to detect market exuberance. Also, a critical review of the several contributions to the literature on the linkages between stock, real estate, and credit markets is undertaken. The empirical analysis is conducted in chapter 3. The procedures and methods applied to answer the research questions are described in subsection 3.1 and the data is detailed in subsection 3.2. Subsection 3.3 presents and discusses the econometric results. Finally, chapter 4 concludes.

2 Bubbles, Contagion, and Financial Stability: A Literature Review

In this chapter, a literature review is made on asset price bubbles. First, a brief historical context about bubbles in the financial markets is presented. Second, the definition and theoretical models that are on the basis of rational and irrational bubbles are discussed. Then, it will be presented not only an expositive approach about the existing literature, but mainly a critical view on bubble detection methods, how to identify asset price misalignments using price-to-fundamental ratios, the relationship between credit, real estate, and stock markets, and the methods to detect cross-market bubble contagion.

2.1 The Prominent Role of Bubbles in Historical Episodes of Financial Crises

The deviation of market prices from fundamental values is not a recent phenomenon as it has been at the epicentre of many financial crises.[1] The first known episode was the so-called "tulip mania" in Holland (Scherbina & Schlusche, 2014). This bubble in tulip markets started in 1634 ignited by the widespread fascination for rare tulip bulbs. A virus infected the bulbs and caused tulips to change to colours never seen before. The rapid increase in its prices attracted speculators and the bubble reached its peak when a single bulb could be sold for an equivalent of 60.000$ today (Scherbina & Schlusche, 2014). This price explosiveness appeared after the emergence of formal future markets that allowed investors to speculate with future prices (Garber, 1989). The bubble burst in 1637 when a plague made investors realise the risk involved in these markets (De Vries, 1976). Since then, many periods of asset price exuberance have occurred, such as the South Sea and the Mississippi bubble in the early 1700s, the 1822-25 Loan bubble over the first Latin American debt crisis, the Roaring Twenties that led to the Great Depression in 1929, among many others throughout the world (Allen & Gale, 2000; Scherbina & Schlusche, 2014).[2]

More recently, the "dot-com" bubble emerged in the stock market and pointed out the relevance of monitoring sector-specific factors. During the period 1998-2000, internet stock prices extended far beyond the stock prices of the other sectors and trading volume of tech stocks reached 20% of the whole stock market (Ofek & Richardson, 2003). However, the great majority of these companies was deeply overvalued since they did not have any tangible

[1] A commonly used definition of asset price bubbles (Blanchard & Watson, 1982).
[2] An example of a bubble episode on the Asian continent was the explosive behaviour of both stock and real estate prices in Japan, in the 1980s.

asset in their balance sheets (Scherbina & Schlusche, 2014).[3] In August 2002, the index declined to values close to the starting point of the bubble (Scherbina & Schlusche, 2014).

Bubble episodes that occur in a specific sector were the result of over-exuberance motivated by business prospects of disruptive innovation, as Zeira (1999) argued. In his model, stock market booms are triggered by informational overshooting when a new technology is introduced in the production process. The market boom remains as long as there is no evidence of its limitations. However, when the limit is reached, agents realise that future growth is no longer possible and prices start to collapse (Anderson, Brooks, & Katsaris, 2010).

The recent global financial crisis has shown how exuberance in financial markets can cause severe costs to economic activity. Output losses, unemployment, bankruptcies, government interventions to avoid bank runs are a few examples of "how costly" this crisis episode was (Claessens, Ayhan Kose, & Terrones, 2010). According to Claessens, Dell'Ariccia, Igan, and Laeven (2010), this period was triggered by the combination of factors that are common to past financial crises and new disruptive conditions.

So, "how similar?". The Great Recession had its roots in a speculative behaviour that led to asset price booms. More specifically, a real estate bubble emerged in the U.S. market and reached a peak of six quarters before the beginning of the crisis (Claessens, Ayhan Kose, et al., 2010). This explosive behaviour in the housing market is remarkably similar to past financial crises, such as the so-called "Big Five" banking crises that happened in advanced countries after the Second World War (Claessens, Ayhan Kose, et al., 2010).[4] Claessens, Ayhan Kose, et al. (2010) also claimed that most economies that have experienced bubble-like behaviour in the housing market were the most affected when they were hit by the contagion effects (e.g. United Kingdom, Spain, Iceland, and many East European countries).

Credit booms are also among the origins of many financial crises and the Great Recession is no exception. The rapid credit growth caused excessive household leverage and put the financial system in danger as financial innovation and low interest rates led banks to search for profitable investments and ease credit conditions. Hence, the credit became vulnerable to subprime loans (Claessens, Dell'Ariccia, et al., 2010). Additionally, as in other financial

[3] Mainly, internet firms only needed a powerful name ended in ".com" to capture the interest of investors during the "dot-com" bubble period.
[4] Spain, 1977; Norway, 1987; Finland, 1991; Sweden, 1991; and Japan, 1992 (Reinhart & Rogoff, 2008).

crises, this episode was also a consequence of a lack of regulation and supervision (Claessens, Ayhan Kose, et al., 2010).

However, "how different" was this crisis? Claessens, Ayhan Kose, et al. (2010) referred to new complex financial instruments with increasing opaqueness (securitisation process), financial integration and interconnectedness, the prominent role of the households, and the excessive leverage of financial institutions and debtors as new dimensions of this financial crisis. In addition, Taylor (2009) emphasized the role of loose monetary policy in the build-up of many vulnerabilities.

2.2 Rational and Irrational Bubbles: A Theoretical Approach

A bubble may be defined as the difference between the market price and the asset's fundamental value (Blanchard & Watson, 1982). It arises when investors buy or hold an overvalued asset because they expect to resell it at a higher price in the future (Brunnermeier, 2017). Therefore, the gap between the price and the value justified by fundamentals can persist over time in a context of rational agents, since they expect potential gains from the increasing gap (Blanchard & Watson, 1982; Diba & Grossman, 1988b).

Rational bubbles occur in a context in which all agents have rational expectations for future earnings and markets are assumed to be predominantly efficient (Wöckl, 2019). In theoretical literature, many seminal papers attempted to explain asset price bubbles in a context of rationality. Just to name a few, Blanchard and Watson (1982), Tirole (1982), Diba and Grossman (1988b), Froot and Obstfeld (1991), and Craine (1993) are among the most cited articles regarding rational bubble models.

Following Scherbina and Schlusche (2014) and Wöckl (2019), rational bubbles may be divided into four categories. First, there is an important distinction based on whether investors are symmetrically or asymmetrically informed. Furthermore, intrinsic bubbles, developed by Froot and Obstfeld (1991), are another specific category of rational bubble models. Finally, agency-based models assume that there are several perverse incentives that rational economic agents need to deal with.

Under specific assumptions, rational bubbles may occur when all agents share the same information. In this case, investors will only hold the overvalued asset if it expands infinitely (Brunnermeier, 2017). Finite lived assets, at the end of the asset's life, T, will be liquidated at its fundamental value. Therefore, since all investors know that the bubble must burst at T, no one is willing to pay more than the fundamental price at T-1 and, hence, it would also burst at T-1. By the same token, a bubble cannot exist at T-2, T-3, and so on (Scherbina & Schlusche, 2014). Hence, bubbles will only survive in infinite lived assets.

In turn, rational bubbles can also emerge under asymmetric information (Brunnermeier, 2017). Although investors know that the asset may be overvalued, they believe that it is not widely known, allowing finite bubbles to exist (Scherbina & Schlusche, 2014). Therefore, an investor holds an overvalued asset as he expects to sell it at a higher price to a fool investor, as a result of asymmetric information on what an investor himself knows about the price and what he thinks the others know (Brunnermeier, 2017).

Froot and Obstfeld (1991) constructed a model in which the bubble component is not a function of time. The bubble component of the asset price is a deterministic function of the fundamentals which led the authors to call it "intrinsic bubbles". This model assumes that asset prices overreact in response to changes in market fundamentals. Conversely, agency-based models propose that bubbles arise in a context of perverse incentives that many economic agents need to deal with (Scherbina & Schlusche, 2014). Herding is an example of that since market participants follow the behaviour of others instead of making decisions based on market fundamentals, because of reputation, limited resources, and relative performance-based compensation (Wöckl, 2019). Limited liability and perverse incentives of information intermediaries are other examples of these models.[5]

Exploring the formal presentation of bubbles, the fundamental component of the asset price can be determined by the present value theory of finance, where it is defined as the sum of the present discount values of expected future cash flows. The fundamental value is derived from the no-arbitrage condition, where the stock price at time t (P_t) equals the expected value at t (E_t) of the sum of the stock price at time t+1 and the generated cash flow at t+1 (CF_{t+1}) discounted to the present using a constant discount rate (r) (Diba & Grossman, 1988a):[6]

2.1. $$P_t = \frac{1}{1+r} E_t(P_{t+1} + CF_{t+1}) \, .$$

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[5] Limited liability allows agents to only face limited downside losses and, on the contrary, benefit of the entire gains which incentives to ride bubbles rather than correcting it (Scherbina & Schlusche, 2014). Moreover, during a rising bubble, equity analysts, accounting auditors, rating agencies and other information intermediaries are reluctant to alert the public of it since they have incentives to profit with the mispricing. See Scherbina and Schlusche (2014) for some explanations.

[6] According to Diba and Grossman (1988a), if the discount rate is time invariant, a bubble can be identified by detecting explosive characteristics in the data.

If we solve 2.1., the fundamental value of the asset can be written as follows:

2.2. $$P_t^f = E_t\left[\sum_{i=0}^{\infty} \frac{CF_{t+i}}{(1+r)^i}\right].$$

However, this form does not allow price to deviate from its fundamentals. If we do not impose the transversality condition

2.3. $$\lim_{k\to\infty} E_t\left[\frac{1}{(1+r)^k} P_{t+k}\right] = 0$$

and considering a process $\{B_t\}_{t=0}^{\infty}$ such that

2.4. $$E_t(B_{t+1}) = (1+r)B_t\ ,$$

prices are composed of the fundamental value and the bubble component (B_t) as follows:

2.5. $$P_t = P_t^f + B_t\ .$$

Equation 2.4. is a crucial condition since the only way that allows the bubble component to persist over time is that this part of the price grows at rate r to compensate the investor for having bought an overvalued asset (Homm & Breitung, 2012; Zhang, 2008). In turn, r must not be greater than the growth rate of the economy to prevent the bubble exceeding the aggregate wealth in the economy (Brunnermeier, 2017).

According to Blanchard and Watson (1982), a realistic form to satisfy equation 2.4. is to consider that the bubble does not necessarily grow forever. Thus, the bubble component may continue increasing with probability π or collapse with probability 1-π:

2.6. $$E_t(B_{t+1}) = \begin{cases} \pi^{-1}(1+r)B_t + \mu_{t+1}\ , & \text{with probability } \pi \\ \mu_{t+1}\ , & \text{with probability } 1-\pi\ , \end{cases}$$

where $\{\mu_t\}_{t=1}^{\infty}$ is a sequence of independent and identically distributed (i.i.d) random variables with zero mean. In addition, Diba and Grossman (1988b) stated that the initial value B_0 should not be zero to allow the bubble to grow.

The formulations presented in 2.4. and 2.6. take into account the explosive process that characterizes bubbles (Diba & Grossman, 1988b). In contrast, Evans (1991) argued that the approach designed by Diba and Grossman (1988b) does not allow to detect periodically collapsing bubbles, and thus he proposed a more prominent process of bubble formation (Waters, 2008). According to Evans (1991), the unit root test proposed by Diba and Grossman (1988a) does not allow to detect periodically collapsing bubbles since the alternative hypothesis they suggested assumes a linear autoregressive process and Evans (1991) concluded that the bubble component follows a nonlinear behaviour.[7]

Nevertheless, there are other approaches to explain asset price bubbles by relaxing the assumption that all investors are completely rational. This refers to behavioural bubble models (often called irrational bubble models). These models assume that rational investors coexist with agents that are influenced by psychological biases (Wöckl, 2019).

In this context, bubbles emerge as a result of psychologically biased traders. Their irrational decisions can be explained by four behavioural models: disagreement-based models, feedback trading, biased self-attribution, and representativeness heuristic and conservatism bias (Scherbina & Schlusche, 2014; Wöckl, 2019). Although rational investors could seize the arbitrage opportunities created by irrational agents, a bubble may survive as there are some limits to eliminate them. The fact that short-sellers face additional costs and risks (both fundamental and synchronization risks[8]) by trading against an overvaluation lead them to trade less than what is needed to eliminate arbitrage opportunities (Brunnermeier & Nagel, 2004; Scherbina & Schlusche, 2014).

The irrational behavioural explained by disagreement-based models assumes that traders have heterogeneous beliefs on asset valuations. Combining this with short-sale constraints, asset price bubbles can occur as a result of optimistic buyers that push prices up, while pessimist traders cannot correct the mispricing as they face short-sale constraints (Brunnermeier, 2017). Feedback trading, as the name suggests, refers to when a specific group of traders (feedback traders) buy assets in response to an initial price increase by basing their decisions on past price movements rather than what is justified by the current valuation. Hence, the price will increase and will attract additional feedback traders, amplifying the mispricing (Wöckl, 2019).

Irrational bubbles can also emerge because of biased self-attribution. In these models, there is a psychological tendency that puts more weight on facts that confirm our own expectations, discarding other relevant information that contradicts our predictions (Daniel, Hirshleifer, & Subrahmanyam, 1998). The bubble burst when the beliefs that caused the price exuberance are reversed (Wöckl, 2019). Finally, representativeness heuristic and

[7] See Evans (1991) and Homm and Breitung (2012) for further details.
[8] Synchronization risk is important in this context since short sellers need a common effort to trade against an overvaluation. If a short seller sells an overvalued asset, but he is not followed by other agents, this arbitrage opportunity will turn to a massive loss. See Abreu and Brunnermeier (2002) for more details.

conservatism bias explain bubbles by the impact of cognitive biases on the probability of an uncertain event (Wöckl, 2019). The representativeness heuristic is a psychological bias in which the probability of an uncertain event is estimated by comparing it to an existing idea that already exists in our minds (more representative) rather than what is more likely to occur. In turn, conservatism bias is the tendency to overestimate pre-existing information in comparison to new evidence (Wöckl, 2019).

2.3 How to Detect Bubbles

2.3.1 Empirical Methods for Bubble Detection

Regarding the above-mentioned formulations, many authors attempted to provide tests for bubble detection. During the 1980s and early 1990s, in-depth research arose to empirically detect rational bubbles. As Gürkaynak (2008) argued and recently followed by Frommel and Kruse (2012) and Wöckl (2019), these early econometric models can be decomposed in three types: variance bound tests, West (1987) two-step tests, and standard stationarity- and cointegration-based tests. The former aim to test whether fundamentals in itself can explain periods of high volatility in stock prices. Hence, variance bound tests are methods used the most to test the validity of the present-value model rather than searching for bubble detection. Shiller (1981) and Leroy and Porter (1981) were the first to show that stock prices are much more volatile than what is justified by fundamentals. However, the violation of the variance bound in these studies was only suggested as a critique of the present-value model (Gürkaynak, 2008). Although Blanchard and Watson (1982) and Tirole (1985) subsequently concluded that the violation of the variance bound can be attributed to bubbles, the result could also be ascribed to the failure of any assumption of the model (Wöckl, 2019).

The model constructed by West (1987) (the second type of models) tried to overcome this problem. The author proposed a method that tests the model and no-bubbles hypotheses sequentially in order to split both tests. If a bubble does not exist, the two estimates should be equal.[9] Since this equality did not hold when applied to the S&P500 index from 1871 to 1980 (annual data) and the Dow Jones index during the period 1928-1987 (annual data), the null hypothesis of no bubble was rejected by West (1987).

[9] The first specification only considers the stock price as a linear relationship with dividends. However, the second one allows the presence of a bubble in the data.

The latter type of models is based on stationarity tests between asset prices and its fundamentals. Unit root tests are often used in this context. These tests check the null hypothesis of the presence of a unit root in the time series against the alternative of stationarity.[10] Campbell and Shiller (1987) applied these formulations to the S&P500 index from 1871 to 1986 and a U.S. Treasury 20-year yield series from 1959 to 1983 and found evidence of a bubble in both datasets. On the contrary, Diba and Grossman (1988a) used a left-tailed augmented Dickey-Fuller (ADF) test and found no evidence of explosive rational bubbles in the S&P500 index during 1871-1986. The ambiguity of the conclusions and the challenges encountered, such as size distortions or the Evans' critique (Evans, 1991) demonstrate that these methods provide unsatisfactory results (Wöckl, 2019).

More recently, there has been a renewed interest in methods for bubble detection. This growing appeal is not only due to the existent gap for further research on these topics but mostly due to the severe consequences of the recent global financial crisis which was founded on bubbles in the financial markets.

The recent methods are based on advanced stationarity- and cointegration-based tests. Unlike standard unit root tests, these advanced methodologies assume that, when a bubble emerges, mildly explosive behaviour must be observed in the data. Hence, the alternative hypothesis is located on the right side of the probability distribution of the test statistic, since these methods test for a unit root (non-stationary process) against an autoregressive process with a root greater but closer to one (Wöckl, 2019). In a nutshell, these methods assume that, if a bubble emerges in the data, asset prices must shift from a random walk to an explosive process. These tests also allow detecting periodically collapsing bubbles, overcoming the main limitations of early bubble detection tests. Recursive unit root tests, fractional integration tests, and regime-switching tests are different approaches for these recent methodologies.

Phillips, Wu, and Yu (2011) were the pioneers in proposing recursive unit root tests to test for asset price bubbles. The novelty of their method is the recursive application of right-tailed unit root tests to subgroups of the entire sample to locate periods of explosive behaviour in the price-to-fundamental data. The authors applied forward recursive regressions of the sup augmented Dickey-Fuller test to the logarithmic NASDAQ

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10 The early unit root tests applied to bubble detection consider a stationary process for the alternative hypothesis which is a left-sided test regarding the probability distribution of the test statistic.

Composite real price and the logarithmic NASDAQ real dividend series from February 1973 to June 2005 (monthly data) and found evidence of a bubble from mid-1995 to sometime between the end of 2000 and the first quarter of 2001.

Instead of identifying the first observation as the initial condition as the previous authors, Phillips and Yu (2011) proposed to make this choice based on an information criterion and applied their method to three time series: monthly U.S. house price-to-rent ratios from January 1990 to January 2009; monthly crude oil prices during the same period; and the spread between Baa and Aaa bond rates from January 3, 2006, to July 2, 2009 (daily data). They detected a bubble period in all time series. Homm and Breitung (2012) concluded that the test proposed by Phillips et al. (2011) has a good performance as a detection mechanism for bubbles. However, they pointed out the higher finite sample power of a Chow-type Dickey-Fuller statistic and a modified version of the Busetti-Taylor test.

Phillips et al. (2011) assumed homoscedastic errors, however, time-varying volatility is a commonly accepted fact in empirical financial data. Therefore, Harvey, Leyboume, Sollis, and Taylor (2016) and Harvey, Leybourne, and Zu (2019) proposed a robust method for bubble detection in the presence of non-stationarity volatility. Hence, they constructed a weighted least squares-based variant of the Phillips et al. (2011) method. Harvey et al. (2019) applied their test to the logarithmic inflation-adjusted FTSE index from December 1985 to December 1999 and S&P500 index during the period 1980-2000, considering daily, weekly and monthly frequencies, and found evidence that their WLS-based test can outperform OLS-based approaches. Also, Astill, Harvey, Leyboume, Sollis, and Taylor (2018) reinforced the importance of building a robust model in case of time-varying volatility, and, following the methodology defined by Astill, Harvey, Leyboume, and Taylor (2017)[11], detected bubble periods in all five major stock market indices[12] using monthly data from January 1995 to January 2002.

According to Phillips et al. (2015), the methodology proposed by Phillips et al. (2011) does not perform well when there are multiple bubbles in the data. To overcome these limitations, the authors extended the model to better suit large time series in which multiple explosive and crisis periods may occur. The method is based on the generalised sup augmented Dickey-

[11] The authors proposed an approach similar to Andrews and Kim (2006) along with the Dickey-Fuller t-ratio for critical value calculations.

[12] DAX30, FTSE All Share, NASDAQ Composite, Nikkei 225, and S&P500.

Fuller test. This version proposes a flexible window width to set up the subsamples in the recursive procedure.[13] The authors detected historical bubble periods by applying their method to the monthly S&P500 price index from 1871 to 2010.

In contrast to unit root tests, fractionally integrated models consider that data has long memory. Koustas and Serletis (2005) stated that these models are suitable for low-frequency behaviour of stock prices, dividends, and their equilibrium relationship. The authors applied their model to the log dividend yield for the S&P500 index and concluded that, since the log dividend yield is a fractionally integrated process, there is no evidence of bubble-like behaviour in the data. Other authors have proposed similar approaches (Cunado, Gil-Alana, & de Gracia, 2005; Frommel & Kruse, 2012). Additionally, regime-switching tests try to find a shift between two regimes: a moderately evolving regime and an explosive and subsequently collapsing regime if a bubble exists (Wöckl, 2019). Some studies have used these models for bubble detection purposes, such as Al-Anaswah and Wilfling (2011), Balke and Wohar (2009), and Schaller and van Norden (2002).

2.3.2 Putting Prices vis-à-vis Fundamentals

Although there is a vast literature on bubble detection, the results depend on the way the model estimates the fundamental value. Once prices deviate from "fundamentals", we cannot guarantee that it was actually a bubble or a wrong specification of the true fundamentals (Gürkaynak, 2008).

2.3.2.1 Stock Market

The great majority of studies that focused on tests for bubble detection in the stock market have used dividends as a proxy for stock's fundamental value. Campbell and Shiller (2001), in line with their seminal contributions about present value models (e.g. Campbell & Shiller, 1988a, 1988b), concluded that dividend-price ratio can forecast movements in stock prices and, therefore, it is a suitable measure to evaluate firms.

As Leone and de Medeiros (2015) stated, dividend-price ratios provide a straightforward comparison between prices and fundamentals. Low dividend yields may indicate a stock price above its earning ability as represented by future dividends. Conversely, high dividend yields could be a sign of an undervalued stock. To check for bubbles, a decreasing trend of the

[13] Section 3.1.1 provides further details about the PSY methodology.

dividend yield can warn of a bubble implosion, since if prices are constantly increasing, at some point dividends should follow up the movement in prices (Leone & de Medeiros, 2015). If that does not happen, it implies that the firm is not able to produce earnings and the increase in prices is not accompanied by its fundamentals, and so a bubble arises (Craine, 1993; Shiller, 1981).

Just to name a few, Campbell and Shiller (1987), Froot and Obstfeld (1991), Shiller (1981), and West (1987) are some examples of early studies that have employed dividend-price ratios to test empirically the presence of rational bubbles in the stock market. More recently, many authors have used the price-to-dividend ratio to search for empirical evidence of rational bubbles in stock market data. For example, Gómez-González et al. (2017), Homm and Breitung (2012), Leone and de Medeiros (2015), and Nneji, Brooks, and Ward (2013) found evidence of rational bubbles by using this ratio as a measure that puts stock price vis-à-vis its fundamentals. In contrast, Koustas and Serletis (2005) used the same ratio but concluded in favour of the absence of rational bubbles in the data. Also, the PSY methodology which will be applied in the empirical analysis of the present dissertation, following Phillips et al. (2011), proposed to use the price-to-dividend ratio in order to detect bubbles in the stock market.

Nevertheless, other ratios can be used for these purposes. Campbell and Shiller (1988b) considered real earnings as well-behaved predictors of firms' present value. This conclusion was reinforced by Campbell and Shiller (2001) who showed that the price-smoothed-earnings ratio is a good valuation measure.[14] Also Fu, Zhou, Liu, and Wu (2020) used price-to-earnings ratio to evaluate the probability of a stock market crisis. Deng, Girardin, Joyeux, and Shi (2017) tested bubble contagion from the stock to the housing market in China between 2005 and 2010 by identifying stock market bubbles using weekly price-to-earnings ratios. In a similar vein, Leone and de Medeiros (2015) used the price-to-earnings ratio as a robustness check of their main analysis based on price-to-dividend ratios. Also, Hu and Oxley (2018) used price-to-earnings ratios to identify stock market bubbles. S. J. Lee, Posenau, and Stebunovs (2020) identified equity market pressures by using both price-to-earnings ratio and dividend yield data. In turn, Herwartz and Kholodilin (2014) concluded that price-to-book ratios have stronger explanatory power for the emergence of asset price bubbles.

All these ratios were proposed to evaluate the stock market as a whole. However, evaluating a firm or a specific sector demands that the specific characteristics of each are considered.

[14] The authors smoothed earnings by considering an average of real earnings in a 10-year period.

Shortly, some issues can undermine the correct valuation of a firm or sector. A specific dividend policy could bias the results that are based on price-to-dividend ratios. An example is the technology sector in which many companies do not pay dividends (Kim & Seo, 2014). Also, the price-to-earnings ratio is likely to pose problems when firms achieve negative earnings over a long period.[15]

Since banks are systemically important institutions, some authors have proposed to study bank bubbles separately and suggested particular market-to-book ratios to evaluate its fundamentals. Bertsatos and Sakellaris (2016) constructed a dynamic model of stock valuation for banks and defined a price-to-book ratio as a positive function of the expected growth of net income and dividend payout ratio, and negatively influenced by the cost of equity. Additionally, Bertsatos, Sakellaris, and Tsionas (2017) tested the impacts of the recent financial crisis on banks' value considering price-to-book ratios as a valuation measure for this specific sector. To check for bank stock bubbles, Cajueiro and Tabak (2006) applied a bilinear test for logarithmic returns of 39 banking stock indices (both developed and emerging economies) from December 1994 to October 2003 (daily data). The authors found strong evidence of rational bubbles in most indices. Also, Miao and Wang (2015) proposed a theoretical model in order to explain the emergence of bank bubbles through a positive feedback loop mechanism.

2.3.2.2 Real Estate Market

As Virtanen et al. (2018) stated, the presence of rational bubbles can also be tested in real estate and credit markets. Many papers have used rents to empirically test real estate bubbles. This choice is based on the discounted cash flow model since rents are the payoffs associated with real estate investments. In this case, rents play the same role as dividends play in the stock market. Several authors have used this argument to advocate the employment of price-to-rent ratios for bubble detection in the real estate market (e.g. Deng et al. (2017), Floro (2019), Gómez-González et al. (2017), Gómez-González, Gamboa-Arbelaez, Hirs-Garzon, and Pinchao-Rosero (2018), Hu and Oxley (2018), Kivedal (2013), Phillips and Yu (2011), and Roche (2001)).

[15] It could be the case of high-tech start-ups which report negative earnings in early life but have strong growth prospects (Bartov, Mohanram, & Seethamraju, 2002).

The real estate market can be divided into residential[16] and commercial properties. As Fabozzi, Kynigakis, Panopoulou, and Tunaru (2020) stated, rents are widely used as proxies for the fundamental value of the real estate market and its variants (both residential and commercial properties).[17] However, these authors emphasised that data on rents may not always be available. Therefore, other measures are also advocated in the literature.

Regarding the residential segment, the price-to-income ratio is a very popular alternative in the literature. This ratio is not only a valuable measure when data on rental markets is not available, but there is also an intuition behind: housing prices cannot increase indefinitely without being followed by income growth, under penalty of deteriorating the housing affordability (Arestis & Gonzalez, 2014; Chen & Cheng, 2017). Previous studies have found empirical evidence of a long-term equilibrium relationship between house prices and income, with both being cointegrated (Black, Fraser, & Hoesli, 2006; Malpezzi, 1999; Renaud, 1989), which suggests it as a reliable valuation measure. For instance, Anundsen et al. (2016) identified housing bubbles by testing for explosive behaviour in house price-to-income ratios of twenty OECD countries from 1975Q1 to 2014Q2.

Some authors have applied tests for bubbles detection to both ratios either as a robustness check or a joint analysis (e.g. Greenaway-McGrevy and Phillips (2016), Pavlidis et al. (2016), and Virtanen et al. (2018)). Vogiazas and Alexiou (2017) found evidence of overvaluation in the residential property market in most of the seven advanced OECD countries considered over 2002-2015 by using both rents and income as housing market fundamentals and concluded that both ratios produce similar results. Moreover, Shi (2017) proposed a composite measure for housing fundamentals. The author combined price-to-rent ratios with some macroeconomic variables such as real per capita income growth, population growth, and employment growth to investigate the existence of speculative bubbles in the U.S. national and regional housing markets during the period 1978-2015.

For the commercial property market, there are also alternatives to rents used in the literature. Since commercial properties are used to produce goods and services and so are mainly owned by companies, using price-to-income ratios may not be a suitable choice to evaluate these properties, as household income does not have a direct impact on its valuation.

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[16] The housing market is the residential property segment of the real estate market.

[17] Hendershott, Hendershott, and Ward (2003) proposed rents as a valuation measure for the commercial property market.

Nneji et al. (2013) identified a commercial property bubble using a composite measure. A bubble was identified with a regime-switching model applied to a U.S. commercial property prices index divided by a combination of the following variables: GDP, long-term interest rates, money supply, term spread, and labour cost. The authors used quarterly data from 1978Q1 to 2012Q1.

In turn, F. Liu, Liu, Malekian, Li, and Wang (2017) considered GDP as the main fundamental to evaluate commercial properties. Besides, the European Central Bank (2010a) considered that commercial real estate is more synchronized with economic activity than the residential market. This study also assumed that disposable income is more suitable for residential properties while gross operating surplus is more adequate for commercial property valuation.

Alternatively, some works propose Real Estate Investment Trusts (REIT) as a proxy for the real estate market (Brooks, Katsaris, McGough, & Tsolacos, 2001; Nneji et al., 2013). A REIT is a company whose core activity is trading commercial real estate properties (Escobari & Jafarinejad, 2016). Since their main revenues are rents and their assets are mostly commercial properties, these companies are significantly dependent on the performance of the real estate market (more specifically, the commercial segment). Although the early research on the relationship between direct and indirect real estate markets reported mixed conclusions, as, on the one hand, some authors concluded that these markets are not close substitutes (e.g. Goetzmann & Ibbotson, 1990; Seiler, Webb, & Myer, 1999) and, on the other hand, others advocated that there is a close link between them (e.g. Clayton & MacKinnon, 2003; Giliberto, 1990), more recent studies provided evidence of a strong nexus between REIT and the underlying real estate market (Bianchi, Guidolin, & Ravazzolo, 2018; Ghysels, Plazzi, Valkanov, & Torous, 2013; M. L. Lee & Chiang, 2010; Nneji et al., 2013). Moreover, some authors have proposed REITs to evaluate the performance of the real estate market, since their stocks are traded on stock exchanges, are more liquid and less costly than other real estate investments, and also have more data available (Ghysels et al., 2013).

For example, Bianchi et al. (2018) investigated whether the burst of the real estate bubble over 2007-2010 was predominantly caused by the performance of the residential property market or the whole U.S. real estate market using REIT data of a large panel of countries from January 1994 to December 2014 and found no evidence of a pure residential real estate bubble during the sample period. Moreover, Ghysels et al. (2013) proposed REITs as an easy alternative to the valuation of the commercial real estate market, mainly because of the complications related to the construction of real estate indices. Carmichael and Coen (2018) proposed to analyse the importance of the property market as a potential risk factor in asset returns determination and used REIT markets to determine the real estate factor.

Also, many tested for the presence of speculative bubbles in the REIT industry, as it is vulnerable to speculations in unsecuritised real estate markets (Bianchi et al., 2018). Brooks et al. (2001) applied variance bound tests to REITs and found evidence of some bubble periods in the United Kingdom (U.K.) real estate market using data from January 1986 to January 1998. Also, Fabozzi et al. (2020) tested for the presence of bubble-like behaviour in the U.S. and U.K. REIT markets from the late 1980s/early 1990s to 2015 and found evidence of explosive processes in both countries. Conversely, Jirasakuldech, Campbell, and Knight (2006) rejected the hypothesis of a bubble in REITs by applying unit root and cointegration tests to U.S. data over 1973-2003.

2.3.2.3 Credit Market

Although credit has supported unprecedented economic growth over the last century, credit bubbles which are defined, according to Mendoza and Terrones (2008), as an excessive credit growth in comparison to economic activity can lead to deep financial crises (e.g. Alessi & Detken, 2018; Reinhart & Rogoff, 2008; Schularick & Taylor, 2012).[18] Jordà et al. (2015) reinforced this argument and stated that "what makes some bubbles more dangerous than others is credit" (p. 1).

Many studies have considered credit-to-GDP ratio as an appropriate measure to identify an overgrowth of credit granted, in line with the previous definition of a credit bubble (e.g. Anundsen et al., 2016; Floro, 2019; Vogiazas & Alexiou, 2017). Alternatively, Korkmaz, Erer, and Erer (2016) found evidence of a credit bubble in Turkey using quarterly data on total credit volume from 1986 to 2014.

However, in accordance with some literature on early warning systems for banking crises, the credit market should be analysed by using a segmented approach (e.g. Anundsen et al., 2016; Büyükkarabacak & Valev, 2010; Virtanen et al., 2018). Anundsen et al. (2016) decomposed the credit market into credit to non-financial enterprises and credit to households and non-profit institutions serving households. For each, the authors

[18] Since in the literature, the term "bubble" is mostly associated with asset prices, credit boom could be a more appropriate expression when referring to the credit market. However, the present work will refer to excessive credit expansion as a credit bubble, following the definition of Mendoza and Terrones (2008).

constructed credit-to-GDP ratios and found evidence that both types of credit have significant positive impacts on the likelihood of a banking crisis. However, they also suggested that household credit has greater marginal effects on the probability of a forthcoming crisis than credit to non-financial companies.

Büyükkarabacak and Valev (2010) also decomposed the credit series and concluded that household credit has robust impacts on the likelihood of a crisis, while corporate credit is less robust. These authors explained the importance of constantly monitoring household credit. On the one hand, the relative weight of household credit on total credit has significantly increased over time, and, on the other hand, this type of credit increases debt levels without necessarily increasing long-term output growth.

Just to mention a few more studies that proposed segmentation of the credit market, Alessi and Detken (2018) proposed to split credit into households and non-financial corporations; Kemme and Roy (2012) used private sector debt as a percentage of GDP as a suitable cause of banking crises; Virtanen et al. (2018) identified credit bubbles by using three different measures: total credit to GDP, bank credit to GDP, and household credit to GDP ratios; and S. J. Lee et al. (2020) identified financial vulnerabilities in terms of leverage by collecting data on bank credit to the private non-financial sector (% GDP), credit to households (% GDP), and equity capital to total assets of the banking system.

2.4 Exploring the Nexus Between Credit, Real Estate, and Stock Markets

As will be discussed below, in the literature on asset market linkages, it is widely accepted that credit, stock, and real estate markets are significantly interconnected.

The reason why credit bubbles often spread to asset markets is commonly explained using the financial accelerator (Bernanke, Gertler, & Gilchrist, 1996, 1999) and leverage cycle (Geanakoplos, 2010) theories. The concept of "financial accelerator" is related to mechanisms by which financial markets amplify the effects of shocks in the economy. These mechanisms generate a feedback loop between the financial sector and the real economy, which may reinforce each other. A positive shock in the credit market (e.g. lower interest rates following a Central Bank's decision) can lead to booms in asset markets as it will cause economic agents to borrow more with the objective of buying more assets (Geanakoplos, 2010). Their balance sheets will increase and hence they may provide more collateral in order to get more credit (Bernanke et al., 1996). The increased demand for assets will result in higher prices. Then, the same process will continue since higher prices will lead to larger collateral and hence to higher credit, and so on. As Geanakoplos (2010) mentioned, leverage plays a central role in the transmission of credit shocks to other markets. During this process, banks also ease credit conditions in order to obtain higher returns, and more leveraged borrowing will be allocated to acquire assets and drive their prices up (Geanakoplos, 2010).[19]

The same process applies to the crash. Once bad news increase uncertainty and market volatility, lenders become anxious and start to demand higher collateral. Credit growth drops and so does the demand for assets. Hence, the lower the demand for assets the higher the reduction in asset prices. During this deleveraging process, leveraged buyers face huge losses and prices continue their downward movement (Geanakoplos, 2010).

2.4.1 Credit and Real Estate

On the basis of the foregoing, credit bubbles can cause a bubble-like behaviour in both real estate and stock markets. When banks grant credit to the private sector, a boom in real estate can emerge in two segments: residential real estate and commercial properties.

As Cerutti, Dagher, and Dell'Ariccia (2017) mentioned, household credit boom is a powerful predictor of housing bubbles. A positive shock in household credit leads individuals to purchase more houses and, hence, it will produce an upward price pressure in the housing market (Arestis & Gonzalez, 2014). Once prices start rising, household balance sheets increase and they can offer more valuable collaterals to obtain more credit (Agnello & Schuknecht, 2011; Herring & Wachter, 2003). Then again, the higher the household credit the higher the demand for houses. With the supply in the housing market being inelastic in the short run, prices keep growing as a result of demand pressure. During this cycle, households become extremely leveraged, often without realising the risks involved as they are living the euphoria of their success (Sornette & Woodard, 2010).

Excessive credit granted to corporations may also contribute to the emergence of a bubble in the residential segment. On the one hand, purchasing and selling houses is the core business of real estate companies. Hence, they resort to credit in order to buy houses that can generate upward pressure on residential property prices. On the other hand, some companies deviate from the core business and invest in the housing market in the search for

[19] During periods of low interest rates, banks are encouraged to make risky and less liquid investments in the "search for yield" (Dombret & Goldbach, 2017).

profitable investments and risk hedging. Therefore, instead of financing their main activities, these firms may use credit to invest in the real estate market (Deng et al., 2017).

Akin, Montalvo, Villar, Peydro, and Raya (2014) suggested a different mechanism by which credit and housing bubbles emerged in Spain from 2005 to 2010. The authors argued that, in Spain, bubble-like behaviour in the housing market was due to bank agency problems. As a response to strong regulation in the banking system, real estate appraisal firms were encouraged to overestimate the real value of the properties to satisfy their clients that are predominantly banks. This ability of banks to influence the valuation of properties by the appraisal firms drives prices up (Bian, Lin, & Liu, 2018). It may also induce a credit boom by the fact that higher prices in the real estate market mean a greater need for credit.

Vogiazas and Alexiou (2017) found evidence that bank credit growth is the basis of housing bubbles which supports the commonly accepted housing price-credit nexus. Real GDP, long-term bond yields and real effective exchange rates are other significant drivers of housing bubbles that authors detected using quarterly data from seven OECD countries (Australia, Belgium, Canada, Denmark, Great Britain, Norway, and Sweden) during the period 2002Q4-2015Q2.

Regarding the commercial real estate market, a bubble may also emerge as a result of a credit boom. As mentioned before, this segment of the real estate market is mostly owned by firms as it is used for the production of goods and services. Therefore, credit to businesses may be channelled into commercial property investments which, in turn, leads to higher property prices. The value of the firms' collaterals starts increasing and allows firms to obtain more and more credit (European Central Bank, 2010b). As a consequence, the cycle continues its self-reinforcing movement. The European Central Bank (2010b) reinforced the important implications that the commercial property market has for financial stability as credit granted to invest in commercial real estate tends to be more volatile which affects bank's portfolio management. Moreover, banks also invest in commercial properties and, considering that this specific segment of the real estate market has implications for the real economy, banks are exposed to both direct and indirect risks (European Central Bank, 2010b).

2.4.2 Credit and Stock

The above-mentioned theories on which the financial cycle is based can also explain how credit booms cause stock market bubbles (Wang & Chen, 2019). The mechanism is similar to that of the real estate market. A positive shock in credit to corporations, which makes access to credit easier and less costly, allows firms to finance their capital projects and increase production capacities (Bernanke et al., 1999). This, in turn, makes firms expand their businesses, which can be conducive to greater profits. As a result, the increase in firms' ability to generate cash flows will lead to an upsurge in their market value (i.e. stock price). Furthermore, the creditworthiness of the companies will increase, leading to higher collaterals and, hence, improve their ability to borrow from a financial institution (Kapopoulos & Siokis, 2005). Firms can also use credit to purchase stocks, thereby contributing to the increase in stock prices. Then again, the collateral value will rise and ease the access to more credit (Fostel & Geanakoplos, 2013).

Credit to households may also stimulate a stock market boom in case of consumer credit. The intuition is clear-cut: credit allows more consumption which in turn boosts firms' sales and profits. Hence, the higher the expected future earnings, the higher the stock price. In the opposite direction of the implication, Poterba (2000) concluded that the stock market performance has a positive impact on consumption.

There is empirical evidence supporting this close link between credit and stock market bubbles. For instance, Wang and Chen (2019) demonstrated that credit as a percentage of GDP and its lagged term are the main drivers of equity bubbles using quarterly data from 22 representative countries, including OECD and emerging economies, over 2000-2018.

2.4.3 Stock and Real Estate

The interconnectedness between the stock and real estate markets is based on a number of transmission channels that are well known in the literature (Changa, Lib, Millerc, Balcilard, & Guptae, 2013; Fan, Li, Shi, & Su, 2018; Liow, Huang, & Song, 2019). The credit-price mechanism[20] has been addressed in this section. This channel explains a unidirectional movement from the real estate market to the stock market. Properties are commonly used as collateral by firms and households while accessing credit. Hence, an increase in property prices will ease borrowing constraints and enable leveraged households and firms to boost consumption and investment which in turn will result in higher stock prices.

[20] Also known as collateral channel (Chaney, Sraer, & Thesmar, 2012).

The second mechanism is the wealth effect. Considering real estate as an investment and a consumption good,[21] an unexpected increase in stock returns as a consequence of a rise in stock prices will lead to an expansion of individuals' wealth, causing an increase in total consumption and hence an expansion of real estate consumptions and prices (Liow et al., 2019). Therefore, this mechanism explains the one-way movement from the stock market to the real estate market. Finally, there is also a substitution effect that drives the relationship between these two markets. This channel is based on the seminal paper on the portfolio management theory of Markowitz (1952). The rationale behind the mechanism is simple: when the stock price goes up, the share of the stock market in the economic agents' portfolios increases. Then, they will rebalance their portfolio by selling stocks and purchasing other assets, such as real estate (Fan et al., 2018). The increased demand for real estate assets will raise property prices. The same holds for the inverse causality.

Deng et al. (2017) and Gómez-González et al. (2017) pointed to another mechanism through which bubbles may transmit from the real estate to the stock market. Deng et al. (2017) called it the expectation formation effect. While prices in the real estate market are increasing and investors expect that they will continue to do so, investing in this market is expected to be profitable. Due to rising investment, a bubble may appear in this market. However, at some moment, the price will be excessively high, and investors realise that this growth is no longer possible. Then, investors will reshape their portfolios by selling real estate assets and investing in other markets. The real estate bubble will disappear as another come up, for instance, in the stock market (Gómez-González et al., 2017).

Several papers have empirically tested the relationship between the stock and the real estate markets. Ali and Zaman (2017) used monthly data on 22 European Union countries from January 2007 to October 2012 and concluded that house prices affect stock prices only in the long-run, however, the opposite causality holds for both the short-run and the long-run. Although the results do not hold for the whole sample period, Changa et al. (2013) found evidence that the U.S. housing market has strong impacts on the stock market, especially during 2007-2010. Fan et al. (2018) also found evidence that the housing market has positive effects on the stock market using data on Chinese housing and stock markets from January 2000 to December 2016. The authors found strong evidence of a reciprocal influence between housing and stock markets. The strong link between these two markets was also

[21] Following the wealth effect theories, stocks do not involve direct consumption (Changa et al., 2013).

confirmed by Hoesli and Reka (2015), Liow (2016), among many others (e.g. Gyourko & Keim, 1992; Hui & Chan, 2014; Lin & Lin, 2011; Okunev, Wilson, & Zurbruegg, 2000). However, Ding, Chong, and Park (2014) found no evidence of a significant causal link from land to stock markets in China during the period 1998-2011. Guo, Chen, and Huang (2011) concluded that the credit default market and the stock market do not affect significantly the real estate market.

Furthermore, a real estate bubble is more prone to occur than stock bubbles due to the prevalence of unsophisticated investors (households), short-sale constraints, and excessive costs to eliminate arbitrage opportunities (Deng et al., 2017; Scherbina & Schlusche, 2014). Gómez-González et al. (2017) added that the housing market is more heterogeneous and depends on subjective individual preferences. Besides, the stock market is easily traded in electronic platforms with high liquidity and trading volume, preventing arbitrage opportunities.

2.4.4 The Central Role of Banks and Conditions for Credit Booms

The emergence of a bubble in the real estate and stock markets caused by excessive credit growth may cause an overvaluation in bank stocks (Herring & Wachter, 2003). On the one hand, banks supply credit against the presentation of appropriate collaterals which may be, for instance, properties or stocks. If prices in these markets are increasing, the value of the collateral is likewise rising. Therefore, not only this allows banks to give more credit as a result of a decline in the perceived risk of lending, but it also raises the value of the existing loan contracts (Herring & Wachter, 2003). Both contribute to the expansion of their profits which may lead to higher bank stock prices. On the other hand, banks also have real estate and equity investments in their balance sheets (Herring & Wachter, 2003). A bubble in these markets lead to the expansion of bank assets and contribute to the emergence of an explosive behaviour of the bank stock prices.

Like the upswing of the financial cycle is a self-reinforcing process with interactions across different markets, similarly, the crash drags every market involved down. This is due to the interconnectedness between them. Thus, when a negative shock brings house and stock prices down and possibly bursts the bubbles, not only the value of the collaterals decreases but more importantly has an adverse effect on economic agents' wealth and income (H. H. Liu & Chen, 2016). Hence, there is an increase in credit delinquencies which dramatically raises uncertainty. While households and firms start failing to repay their loans, banks tighten credit conditions and launch a deleveraging process to minimise losses (Cunat, Cvijanovic, & Yuan, 2018; H. H. Liu & Chen, 2016). This process reinforces the downward pressure on asset prices and bank stocks tread the same path (Hott, 2011). In sum, the banking sector can stimulate the advent of a bubble in the real estate and stock markets, but also the burst of these bubbles can damage the entire banking system (Ahn, Jang, Sohn, & Song, 2018).

Martin and Ventura (2015) constructed a model to explain how credit bubbles arise. They found that financial globalization and low interest rates create a boom-friendly environment that can trigger an upswing in the credit market. Korkmaz et al. (2016) concluded the same and stated that interest rates have a negative impact on the probability of a credit bubble.

Martin and Ventura (2015) showed that a credit boom may not be the causal effect that triggers a bubble-like behaviour in the economy. It can be only a mechanism through which the shock is amplified. They showed that low interest rates lead to asset price bubbles, which in turn raises the value of the collaterals and allows banks to ease borrowing constraints. Therefore, the initial shock may fuel a credit boom. The rationale behind this approach may be seen in the well-known Minsky (1986) model. Accordingly, the bubble dynamics is divided into five phases: the displacement phase, during which appear technological or financial innovations;[22] the boom phase, when there are strong increases in investment as more participants enter the market, a significant credit expansion, and low volatility; the euphoria phase, characterized by over-optimistic investors that lead to high trading volume and price volatility; the profit-taking phase, when sophisticated investors start taking their profits and reduce their positions; and finally, the panic phase, when agents try to get rid of riskier investments causing a sharp fall of its prices.

2.5 Bubble Contagion: Methods and Empirical Evidence

As the present work is focused on bubble transmission, some related concepts will now be clarified. There is a significant difference between spillover, migration, and contagion effects, though they are often mixed up. A spillover effect is closely related to externalities and occurs mainly when what happens in one context affects a seemingly unrelated context (Hu & Oxley, 2018). In a nutshell, a spillover is a consequence of the functioning of a market that has an impact on the running of another. In turn, in related contexts, migration refers to the movement of assets' characteristics (e.g. price, expected profitability, riskiness) that flows

[22] Lower interest rates can be an example of such innovations, which sow the seeds for the subsequent bubble.

from one market to another (Hu & Oxley, 2018). Migration includes the effects that one market may cause on other markets and usually occurs as a result of interconnectedness (or interdependence (Forbes & Rigobon, 2002)) between them (Hu & Oxley, 2018). However, none of these definitions suits the objectives of the present work. Conversely, contagion is defined as a substantial increase in cross-market linkages following a shock in a specific country or asset (Forbes & Rigobon, 2001).[23] As will be explained in chapter 3, the definition of bubble contagion relies on the transmission of explosive behaviour in asset prices from one market to another, which should increase when bubbles merge and should decline after bubbles burst (Hu & Oxley, 2018).[24]

In light of the interconnectedness mentioned in the previous section, the present work aims to test for cross-asset bubble contagion. That is, since the emergence of multiple bubbles in asset markets and a rapid credit boom threatens the stability of the financial system as mentioned before (e.g. Anundsen et al., 2016; Jordà et al., 2015; Schularick & Taylor, 2012; Virtanen et al., 2018), it is far more important to investigate by which segments a bubble-like behaviour transmits from one asset to another than to simply explore the causality nexus between markets regardless of whether there is a bubble in the data or not, though both approaches are related. Identifying co-movement patterns across markets could be truly relevant for portfolio management purposes. However, bubble contagion may be important for monitoring the build-up of vulnerabilities that can threaten financial stability.

To test for the presence of bubble contagion effects between different markets, Phillips and Yu (2011) proposed a model that first detects an explosive behaviour in each market by using the right-tailed unit root test suggested by Phillips et al. (2011) and then applies a recursive method to identify the transmission of that explosive movement in asset prices across different markets. The authors assumed that the contagion effects are time-invariant across the housing market, crude oil market, and spread between Baa and Aaa bonds. Using data on U.S. price-to-rent ratios from January 1990 to June 2009, monthly crude oil prices divided by oil supply (approximated by the U.S. inventory) during the period January 1999 – June 2009 and daily spreads between Baa and Aaa bonds from January 3, 2006, to July 2, 2009,

[23] This definition of contagion does not find universal acceptance. In some literature, contagion is defined as cross-market transmission effects regardless of whether it occurs after a shock or in more tranquil periods (Forbes & Rigobon, 2001).

[24] Since the transmission effects are detected by searching for an increase in the interlinkages between different markets after a bubble is observed, then the term "contagion" is the one that best suits the objectives of the present work. For example, Greenaway-McGrevy and Phillips (2016) used the same terminology.

Phillips and Yu (2011) concluded that a bubble period emerged in the housing market and then spread to crude oil and bond markets during the build-up phase of the Great Recession.

The same method was used by Gómez-González et al. (2017) to test for cross-market bubble contagion. They applied it to a panel dataset on housing, stock, and currency markets of seven countries (Colombia, Holland, United Kingdom, South Africa, Portugal, South Korea, and Canada). The housing market was analysed from the behaviour of price-to-rent ratios over the period from January 1986 to December 2013.[25] Price-to-dividend ratios were used for detecting stock market bubbles during May 1993 – December 2013. For the currency market, this study used the relationship between the consumer price index (CPI) of each country and the U.S. CPI from January 1990 to December 2013. The authors found several transmission episodes between these markets.

Based on this method, Greenaway-McGrevy and Phillips (2016) constructed a model that allows for time-varying transmission effects between different markets, which fits the data quite well.[26] They applied the methodology to check for bubble contagion across different geographical regions in the New Zealand housing market by checking the significance of the intensity of bubble transmission effects, which may take an inverted U-shape, as it is reasonable to expect that, when two bubbles merge, the contagion effects should increase and then decrease after the bubble burst (Gómez-González et al., 2018; Greenaway-McGrevy & Phillips, 2016).

Other authors have followed their work and applied it to different markets (both cross-asset and cross-border transmission). Deng et al. (2017) applied this method to the stock and housing markets in China between 2005 and 2010 and found evidence of bubble contagion from the former to the latter in 2009 and a temporary transmission in 2007. Hu and Oxley (2018) followed the same method to test for bubble transmission from the stock to the real estate market in Japan during the period 1970Q1-1999Q4. The authors concluded that a bubble in the stock market has transmitted to the real estate market during this well-known bubble period in Japan. Gómez-González et al. (2018) used this methodology to check for cross-border bubble contagion. They found five episodes of transmission from the U.S. housing market to other OECD countries (mostly European countries) from 1970 to 2015 (quarterly data). Gómez-González and Sanin-Restrepo (2018) also applied this bubble

[25] The size of the sample varies across countries, so only the largest time series from all countries is mentioned.
[26] Section 3.1.2 provides further details about bubble contagion tests.

contagion test on monthly price-to-rent ratios of Canadian provinces from January 1986 to June 2017. These authors found evidence of a centre-periphery bubble contagion.

Other methods have also been used in the literature to test for bubble contagion. For example, Kohn and Pereira (2017) tested bubble contagion between the American and European stock markets by implementing three different models (Dynamic Conditional Correlation (DCC)-GARCH, Constant Conditional Correlation (CCC), and Varying Conditional Correlation (VCC)) in order to analyse which one has the best performance. The authors used daily data of S&P500, Dow Jones Industrial Average, Nasdaq Composite, FTSE100, DAX, and Euro STOXX indices from December 1, 1990, to December 31, 2014. According to these authors, all models confirmed the presence of bubble contagion between those stock markets during the "dot-com" period.

In turn, He, Qian, Fei, and Chong (2019) developed a duration dependence test for detecting bubbles in the Chinese stock market. They implemented an industry level approach and, using weekly data from January 4, 2002, to December 31, 2013, found evidence of bubble contagion from the telecommunications sector to the health care industry. Teng, Chang, and Chen (2017) proposed a different approach to test for bubble contagion in the housing market from Taipei City to the suburbs during 1973-2014. They applied an Engle-Granger cointegration test to the housing, fundamental, and bubble prices and concluded that the housing and bubble prices of the centre and periphery cities are cointegrated, but fundamental prices are not. Since the Granger causality of bubble prices from the central city to the suburbs is much more significant than that of the fundamental prices, they found that housing bubbles transmit across regions.

In a nutshell, there is no empirical work that has focused on detecting bubbles and its contagion between stock, real estate, and credit markets taken together and, even more novel, there is not any relevant study that analyses bubble contagion between different segments of these crucial markets for financial stability, neither using the methodology proposed by Greenaway-McGrevy and Phillips (2016) nor other methods. Moreover, this methodology to detect bubble contagion has two main advantages. First, this method relates with the PSY methodology for bubble detection, which allows pursuing tests for bubble transmission using the PSY tests that are commonly used in the recent literature on bubble detection. Second, this method accommodates time-varying contagion effects, which is much more realistic than the method proposed by Phillips and Yu (2011).

3 Empirical Analysis: Bubble Detection and Contagion

The present chapter investigates empirically the detection of explosive bubbles in stock, real estate, and credit markets, and analyses contagion between them. Specifically, an analysis of segments of each market is proposed to shed light on the transmission effects across them. First, the methodological framework is presented, describing the procedures that allow detecting bubbles in the data and then assessing the potential contagion of bubble-like behaviour between the markets analysed in the present work. The data is presented in subsection 3.2. Finally, subsection 3.3 presents and discusses the econometric results.

3.1 Methodology

3.1.1 Bubble Detection

The presentation of the PSY methodology for bubble detection requires recalling some of the equations presented in the previous chapter. Considering equation 2.2., and replacing it in equation 2.5., it is possible to obtain the asset pricing equation upon which the analysis of asset price bubbles is based (Blanchard & Watson, 1982):

3.1. $$P_t = E_t\left[\sum_{i=0}^{\infty} \frac{F_{t+i}}{(1+r)^i}\right] + B_t \ .$$

In equation 3.1., a more general formulation was introduced by considering that the price depends on the expected value of future fundamentals (F_t) and the bubble component (B_t).

The submartingale process included in equation 2.4. defines that the bubble component follows an explosive behaviour which forces prices to be equally explosive in the presence of bubbles (Phillips et al., 2015; Phillips et al., 2011).[27] [28] This assumption is crucial to the model. In the absence of the bubble component, the asset price behaviour is entirely determined by the fundamental series. It is commonly assumed in the literature that the fundamentals follow a random walk with a negligible drift and, therefore, if B_t=0, asset prices (and hence price-to-fundamental ratio) should exhibit a similar process (Phillips et al., 2015; Phillips & Yu, 2011; Virtanen et al., 2018). Therefore, when fundamentals are at most I(1),[29] an explosive process in asset prices or price-to-fundamental ratios may be considered as

[27] A submartingale is a stochastic process in which the expectation for the next value of the sequence is greater than or equal to the value of the current period (Charemza & Deadman, 1995).
[28] Assuming a positive discount rate.
[29] I(d) means integration of order d. The order of integration (d) represents the minimum number of differences required to have a stationary process. If a time series is integrated of order one (I(1)), then the stochastic process has a unit root (Dickey & Fuller, 1979).

evidence of the existence of bubbles in the data (Pavlidis et al., 2016; Phillips et al., 2015; Phillips et al., 2011).

Asset prices may deviate from their fundamental value as a result of multiple causes. Although commonly applied to rational bubbles, the reduced-form approach presented here accommodates other mechanisms through which bubbles may emerge in the markets. According to PSY, this method can detect bubbles caused by shocks in fundamentals, called intrinsic bubbles (Froot & Obstfeld, 1991), behavioural factors such as herding (Abreu & Brunnermeier, 2003), and time-varying discount rates (Phillips & Yu, 2011).[30]

Therefore, the method proposed by PSY is based on right-tailed unit root tests in order to detect a switching point from a martingale process in the price-to-fundamentals ratio to mildly explosive behaviour. Hence, the null hypothesis is defined as a martingale process with a negligible drift, since, in the absence of bubbles, asset prices and price-to-fundamentals ratio has the same degree of nonstationarity as the fundamental component (Phillips et al., 2015). The following equation presents a prototypal formulation of the null that accounts for the above-mentioned specifications (Phillips et al., 2015):

3.2. $$H_0: y_t = dT^{-\eta} + y_{t-1} + \varepsilon_t \,, \qquad \varepsilon_t \sim N(0, \sigma^2),$$

where y_t is a generic time series, d is a constant, η is greater than 1/2 [31] and T is the total sample size. Conversely, to test for the presence of bubbles (i.e. $B_t>0$), the alternative hypothesis is a mildly explosive process (Phillips et al., 2015):

3.3. $$H_1: y_t = \delta_t y_{t-1} + \varepsilon_t \,,$$

assuming $\delta_t=1+cT^{-\theta}$ with c>0 and $\theta \in (0,1)$.

More specifically, the PSY methodology proposes to recursively apply ADF tests on subsamples of varying size using the following regression:

3.4. $$\Delta y_t = \alpha_{r1,r2} + \beta_{r1,r2} y_{t-1} + \sum_{i=1}^{k} \gamma_{r1,r2}^{i} \Delta y_{t-i} + \varepsilon_t \,, \qquad \varepsilon_t \sim N(0, \sigma^2).$$

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30 Phillips and Yu (2011) concluded that changes in the discount rate may induce bubbles in asset prices. However, assuming the discount rate to be time-invariant does not have implications for the analysis of the submartingale process given in the equation 2.4. (Phillips et al., 2011; Phillips & Yu, 2011).

31 η is a parameter that affects the magnitude of the intercept and drift as $T \to \infty$. Assuming $\eta>1/2$ guarantees that the drift is small in comparison to the martingale component, which meets the evidence that a random walk with a negligible drift fits the data on the fundamental component of asset prices (Phillips et al., 2015).

where y_t, although here it is not a specific variable, will denote the price-to-fundamental ratio, k is the lag order, r_1 and r_2 are respectively starting and ending points of a subsample period, and $\alpha_{r1,r2}$, $\beta_{r1,r2}$ and $\gamma^i_{r1,r2}$ with i=1, …, k are regression coefficients. Considering this formulation, the emergence of bubbles in the data is detected by a shift from a random walk to a mildly explosive process and, therefore, the null hypothesis means that y_t has a unit root, H_0: $\beta_{r1,r2} = 0$, and the alternative accounts for a mildly explosive behaviour, H_1: $\beta_{r1,r2} > 0$.

The generalised sup augmented Dickey-Fuller (GSADF) test is applied for testing these hypotheses. It is based on a rolling window technique in which both the onset and the end of the subsamples vary within a feasible range.[32] The endpoint r_2 varies from r_0 to 1, where r_0 is the minimum window size, and the starting point changes from 0 to r_2-r_0.[33] The GSADF statistic is specified as the t-ratio of the Ordinary Least Squares (OLS) estimate of $\beta_{r1,r2}$ and is the largest ADF statistic (supremum) over r_w:

3.5. $$GSADF(r_0) = \sup_{\substack{r_2 \in [r_0, 1] \\ r_1 \in [0, r_2 - r_0]}} \left\{ADF_{r_1}^{r_2}\right\}.$$

According to PSY, the distribution of the GSADF test statistic is the following:[34]

3.6. $$\sup_{\substack{r_2 \in [r_0, 1] \\ r_1 \in [0, r_2 - r_0]}} \left\{ \frac{\frac{1}{2} r_w \left[W(r_2)^2 - W(r_1)^2 - r_w\right] - \int_{r_1}^{r_2} W(r)dr\left[W(r_2) - W(r_1)\right]}{r_w^{1/2}\left\{r_w \int_{r_1}^{r_2} W(r)^2 dr - \left[\int_{r_1}^{r_2} W(r)dr\right]^2\right\}^{1/2}} \right\},$$

where W is a Wiener process.[35]

It is worth noting that r_0 is not arbitrarily chosen, so its setting depends on the total number of observations T. First of all, it must be large enough to allow for adequate initial estimations. On the other hand, if it is too large, it may miss an early explosive episode. Accordingly, based on several simulations, PSY recommended the following rule:

3.7. $$r_0 = 0.01 + 1.8/\sqrt{T}.$$

[32] $r_w = r_2 - r_1$ defines the window size of the subsample, which is a fraction of the whole sample.
[33] See Appendix A1 for an illustration of the procedure.
[34] For further details, see Phillips et al. (2015) (PSY).
[35] Often called Brownian motion.

However, the GSADF test is not able to provide the origination and termination dates of detected bubbles, since it only tests for the presence of at least one bubble episode in the whole sample.[36] Once the null hypothesis of a unit root in y_t is rejected, the PSY method proposes a dating strategy that performs a recursive evolving algorithm. In particular, a sup ADF test is applied to a backward expanding subsample sequence (BSADF). Differently from the GSADF test for bubble detection in the whole sample, this date-stamping strategy kept fixed the endpoint of each subsample (r_2) and only allows r_1 to vary from 0 to $r_2 - r_1$.[37] Therefore, the origination date of a bubble is identified at the first observation whose BSADF statistic exceeds its critical value, and the termination date is defined as the first observation after the starting date whose BSADF statistic falls below its critical value. This procedure also detects very short-lived bubbles, so Phillips et al. (2015) propose to only consider bubble episodes that exceed the quantity log(T). Therefore, only bubbles with a duration of at least three quarters are reported. Additionally, note that this method allows detecting both positive and negative bubbles (Gómez-González et al., 2018). Therefore, when an explosive downward movement is detected in the price-to-fundamental time series, a crisis period is identified.

In addition, the lag order is set in accordance with the Bayesian information criterion (BIC).[38] [39] Moreover, the finite sample critical values are obtained by a wild bootstrap scheme. Since Harvey et al. (2016) demonstrated that, in the presence of non-stationary volatility, the Monte Carlo simulations proposed by PSY can lead to oversized results, the present work proposes to obtain the critical values for the GSADF test by using 2000 bootstrap replications as it accounts for heteroskedasticity and multiplicity issues (Phillips & Shi, 2018, 2019).

3.1.2 Bubble Contagion

To analyse bubble transmission across markets, the present work applies the method proposed by Greenaway-McGrevy and Phillips (2016). Their method is based on Phillips and Yu (2011), however, a more realistic extension was added. Greenaway-McGrevy and

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[36] Detected when the t-ratio exceeds the right-tailed critical value obtained from the equation 3.6.
[37] See Appendix A1 for a visual presentation.
[38] Also known as Schwarz information criterion (Schwarz, 1978). The choice of this criterion to select the optimal lag length k is a common practice in the literature that make use of the PSY methodology to detect bubbles in the data (e.g. Astill et al., 2018; Fabozzi et al., 2020; Gómez-González & Sanin-Restrepo, 2018; Harvey et al., 2016; Leone & de Medeiros, 2015; Phillips & Shi, 2018; Shi, 2017; Virtanen et al., 2018).
[39] According to Phillips et al. (2015), the longer the lag length, the greater the size distortions of the GSADF test. Therefore, following Fabozzi et al. (2020) and Pavlidis, Martínez-García, and Grossman (2019), in the present work, the maximum lag length is set to four quarters.

Phillips (2016) proposed a method in which the cross-market contagion effects vary over time. In fact, markets are characterised by heterogeneity and time-varying intensities of transmission effects (Gómez-González et al., 2018).

Let $\{\hat{\beta}_{core,s}\}_{s=S}^{T}$ and $\{\hat{\beta}_{j,s}\}_{s=S}^{T}$ be the slope coefficient sequences obtained from moving window regressions of equation 3.4. with a fixed window size of S, where core is the core market from which the asset bubble is hypothesised to originate and j the recipient market. In order to analyse the contagion effects from the core market to market j, Greenaway-McGrevy and Phillips (2016) proposed a nonparametric regression:

3.8. $$\hat{\beta}_{j,s} = \delta_j + \gamma_j\left(\frac{s}{T-S+1}\right)\hat{\beta}_{core,s-d} + \varepsilon_s\,, \qquad \forall j \neq core, \qquad s = S, \dots, T$$

where d is the delay parameter that accommodates the lag in the contagion effects from the core market to other markets, s is the observation that corresponds to the ending date of the subsample, S is the ending date of the initial subsample, hence, it defines the window size of each subsample, as it is assumed to be fixed, and ε_s is the error term.

The coefficients $\hat{\beta}_{i,s}$ are obtained by a least squares estimation of the equation 3.4. as previously mentioned. Since equation 3.11. is a nonparametric regression, the coefficient γ is estimated by a local-level kernel regression (Greenaway-McGrevy & Phillips, 2016):

3.9. $$\hat{\gamma}_j(r; h, d) = \frac{\sum_{s=S}^{T} K_{hs}(r)\tilde{\beta}_{j,s}\tilde{\beta}_{core,s-d}}{\sum_{s=S}^{T} K_{hs}(r)\tilde{\beta}_{core,s-d}^{2}}\,, \qquad \tilde{\beta}_{i,s} = \hat{\beta}_{i,s} - \frac{1}{T-S+1}\sum_{s=S}^{T}\hat{\beta}_{i,s}$$

where $K_{hs}(r) = \frac{1}{h}K\left(\frac{s/T-r}{h}\right)$ with $K(.) = (2\pi)^{-1/2}e^{-\frac{1}{2}(.)^2}$ which is the Gaussian kernel, $\tilde{\beta}_{i,s}$ are mean-corrected coefficients and h is a bandwidth parameter.[40]

According to most papers that used this methodology (e.g. Deng et al., 2017; Gómez-González et al., 2018; Gómez-González & Sanin-Restrepo, 2018; Greenaway-McGrevy & Phillips, 2016), a one-year range is settled for the delay parameter d, i.e., d∈{0,1,…,4}. Also, following equation 3.7., it is assumed S=26 quarters.

Note that the autoregressive coefficients $\hat{\beta}_{i,s}$ (i=core, j) are the basis of the bubble test proposed by PSY and, hence, to some extent, denote the degree of exuberance in the data (Greenaway-McGrevy & Phillips, 2016). Therefore, the time-varying coefficient γ measures

[40] Details of the selection of the bandwidth and the lag order are given in the Appendix A2.

the transmission effect from the originating country to the recipient. The intention is to examine how the coefficient γ behaves during periods in which bubbles are detected. It is expected that this coefficient has an inverted U shape when exists bubble contagion, since the transmission effects should intensify when two bubbles merge, before reaching a maximum. Then, when bubbles burst, contagion effects should decline. These conclusions are unanimous in the literature on bubble contagion that has followed this methodology to detect it (e.g. Gómez-González et al., 2018; Gómez-González & Sanin-Restrepo, 2018; Greenaway-McGrevy & Phillips, 2016; Hu & Oxley, 2018).

3.2 Data

The present work proposes to detect bubbles and their contagion effects between different segments of the stock, real estate, and credit markets. Also, the present work aims to study the U.S. markets, for the reasons that were presented in the introduction, and the U.S. only.

As mentioned before, the results of the unit root tests for bubble detection proposed by Phillips et al. (2015) depend on the selection of the valuation measures for each market. That is, one needs to select price-to-fundamental ratios to perform these tests. Thus, this subsection presents the choice of the valuation ratios and brief analysis of each time series.

Table 1 summarizes the data used in the present work. The sample comprises quarterly data from 1980Q1 to 2019Q4, totalling 160 observations. The choice of the sample period was based on data availability. However, as Virtanen et al. (2018) highlighted, using data from 1980 onwards also allows us to overcome some bias due to structural changes that occurred in the financial system during the 1970s. The valuation ratios to apply the bubble detection tests were selected according to the existing literature and the specificities of each market. For the non-financial stock market, the present work considers the price-to-dividend ratio obtained from the inverse of the dividend yield, following several papers that tested for bubbles in the stock market (e.g. Froot & Obstfeld, 1991; Gómez-González et al., 2017; Homm & Breitung, 2012; Phillips et al., 2015). Differently, the price-to-book ratio is used for the case of bank stocks, following Jordan, Rice, Sanchez, and Wort (2011). I also analysed banks' price-to-dividend and price-to-earnings time series. However, since during the crash of the banking system in 2008 dividends and earnings have fallen much more than bank stock prices, the ratios exhibit bubble-like behaviour over 2008-2009 which is not consistent with what occurred during this episode.[41] Therefore, using price-to-book data, a collapse is clearly identified in 2008, as expected.

Table 1. Summary of the data

Market	Valuation Measure	Sample Period	Source
Non-Financial Stock Market	Price-to-dividend	1980Q1-2019Q4	Datastream
Bank Stock Market	Price-to-book	1980Q1-2019Q4	Datastream
Residential Property Market	Price-to-rent	1980Q1-2019Q4	OECD Analytical House Price Indicators
Commercial Property Market	Price-to-dividend	1980Q1-2019Q4	Datastream
Credit to Household	Credit-to-GDP	1980Q1-2019Q4	Bank for International Settlements
Credit to Non-Financial Corporations	Credit-to-GDP	1980Q1-2019Q4	Bank for International Settlements

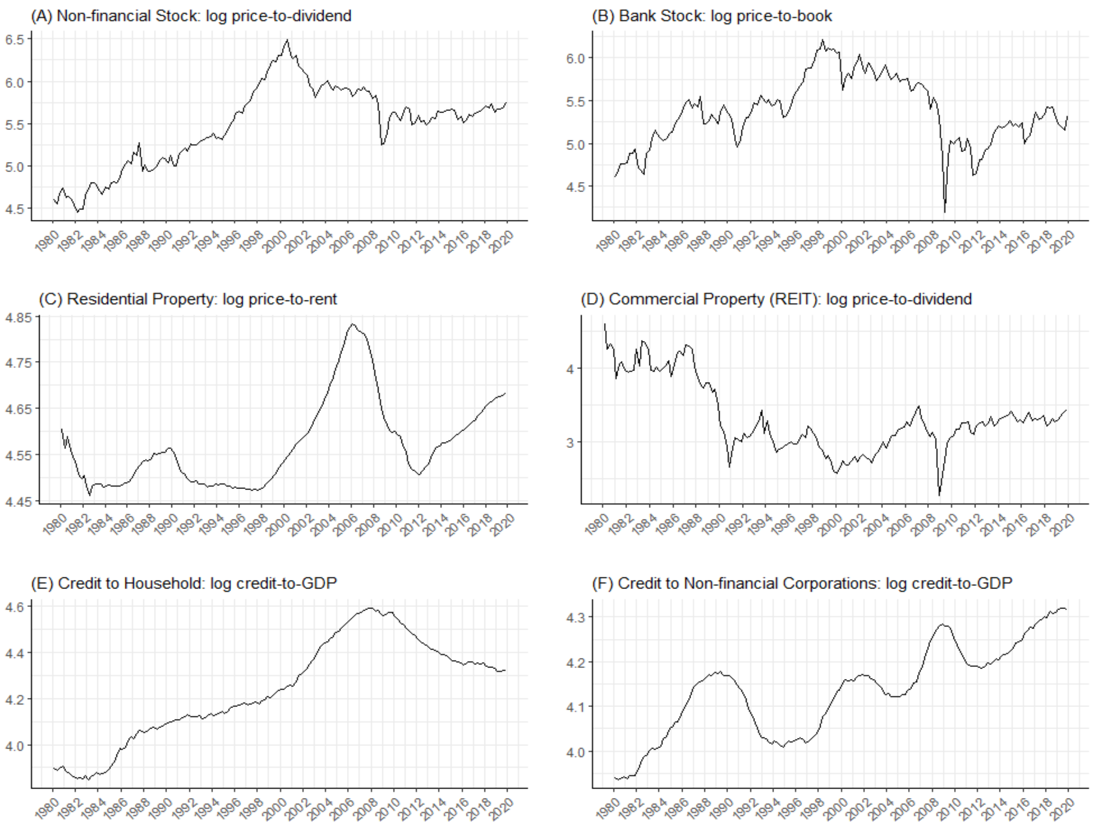
To check for housing bubbles, a vast number of papers have used price-to-rent data to evaluate the real estate market (e.g. Deng et al., 2017; Gómez-González et al., 2018; Gómez-González et al., 2017; Greenaway-McGrevy & Phillips, 2016; Hu & Oxley, 2018; Phillips & Yu, 2011; Roche, 2001). However, rental data is not available for the commercial segment. Therefore, following relevant literature (Bianchi et al., 2018; Brooks et al., 2001; Carmichael & Coen, 2018; Ghysels et al., 2013; Nneji et al., 2013), the present work considers the REIT market as a proxy for the commercial property market. Thus, the price-to-dividend ratio is used as a valuation measure, following Joyeux and Milunovich (2015) and Nneji et al. (2013). Finally, as proposed by Anundsen et al. (2016), for each segment of the credit market in analysis, the bubble detection tests are applied to the household credit-to-GDP ratio and credit to non-financial corporations as a percentage of GDP, respectively. In addition, bubble detection tests are commonly applied to log-transformed price-to-fundamental ratios (e.g. Deng et al., 2017; Gómez-González & Sanin-Restrepo, 2018; Greenaway-McGrevy & Phillips, 2016; Hu & Oxley, 2018; Phillips & Shi, 2019). Therefore, in the present empirical analysis tests are computed after taking logarithms.

Figure 1 displays log price-to-fundamentals for each market over the sample period.[42] The recent crisis is evidenced to a greater or lesser extent by all markets as a sharp downturn may be found in all time series over 2008-2009. Moreover, the well-known housing exuberance

[41] See Appendix A3 for a visual inspection of this argument.
[42] See Appendix A4 for the display of price-to-fundamental ratios in levels.

reinforced by the household credit before the Great Recession is clearly noticeable (Panel (C)).

Figure 1. Price-to-fundamental ratios by market (in logarithms)



Furthermore, a steep increase of the price-to-dividend in the non-financial stock market (Panel A) that peaks around 2000 is consistent with the "dot-com" bubble period. The credit to non-financial corporations (Panel F) exhibits a boom over four different periods. First, a significant increase occurred in the late 1980s which drops throughout the economic recession in the U.S. economy in the early 1990s. A second upsurge occurred during the "dot-com" bubble fuelling the exuberance in the stock market. Third, a large expansion may be seen before the Great Recession. More recently, the ratio follows an upward movement, hitting a historic high. The following section tests whether these periods are identified as bubbles or not.

3.3 Empirical Results: Testing for exuberance and contagion

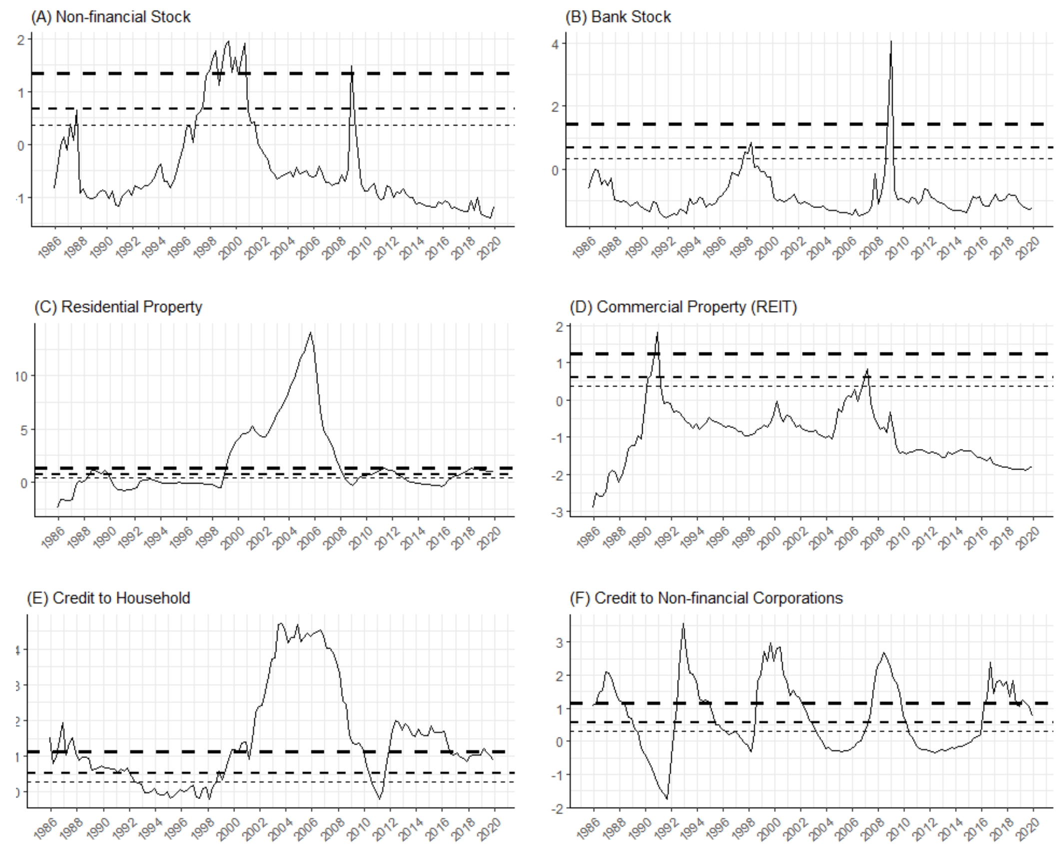
This section starts by detecting bubbles in the aforementioned markets applying the PSY tests. Based on the detected bubbles, I then examine the bubble transmission by estimating the time-varying contagion coefficient following Greenaway-McGrevy and Phillips (2016).

3.3.1 Bubble Detection and Date-Stamping

Following the PSY methodology, recursive right-tailed unit root tests are applied to subsamples with varying sizes to detect a switching point from a random walk in the valuation ratio to mildly explosive behaviour. Therefore, bubble periods are detected when the BSADF statistic of the above-mentioned tests exceeds the critical values and so an explosive process is identified. In the present work, these tests are applied to the log of the valuation measures presented in Table 1.

Figure 2 exhibits the results of the BSADF tests that allow detecting bubble episodes. As mentioned in subsection 3.1, these tests detect both positive and negative bubbles. Hereafter, I will refer to positive bubbles as bubble periods and to negative ones as crisis episodes.

Figure 2. Results of the BSADF tests for each market



Notes: The solid line is the BSADF statistics and the dashed lines are the 90% (lower width), 95%, and 99% critical values.

Test statistics are significantly greater than the critical values even at the 1% significance level and therefore at least one exuberance episode was found in each market. However, following Phillips et al. (2015), short-lived bubbles are discarded, so just bubble or crisis episodes with a duration of at least three quarters are considered. Some markets record high value of the

BSADF statistics, thereby rejecting the null hypothesis at extremely high confidence levels. The residential real estate market is the one that exhibits the highest value of the test statistics, signalling a huge housing bubble in the early 2000s that peaked before the beginning of the Great Recession.

Table 2 presents the periods in which the BSADF test detects exuberance in the data, taking 90% critical values. In both segments of the stock market, this procedure detected a bubble episode during the "dot-com" bubble. However, looking at figure 2, this bubble in the stock market is much more significant in the non-financial segment than in the banking sector, as it is identified at higher critical values in the former. These results are consistent with the fact that the "dot-com" bubble was predominantly observed in the technology sector, as a result of exuberance and excessive optimism around technology firms, as explained in section 2. Therefore, although a short bubble period was detected in the bank stock market (only at 10% significance level), this episode was much more sizable in the non-financial segment, as the test statistic shows. It is worth mentioning that this procedure also detected a crisis episode during 2008-2009 as expected since a crash occurred in the financial system. However, these episodes are not included in the table as they only lasted for two quarters (2008Q4 to 2009Q1).

Table 2. Bubble and crisis periods

Market	Bubble Episodes		Crisis Episodes	
	Periods (90% critical values)	**Total Quarters**	**Periods (90% critical values)**	**Total Quarters**
Non-Financial Stock Market	1996Q4-2001Q2	19		
Bank Stock Market	1997Q4-1998Q2	3		
Residential Property Market	1988Q2-1989Q4 1998Q4-2008Q1 2016Q3-2019Q4	59	2009Q2-2012Q4	15
Commercial Property Market			1990Q1-1991Q1	5
Credit to Household	1985Q4-1992Q1 1998Q4-2010Q2	73	2011Q3-2019Q4	34
Credit to Non-Financial Corporations	1985Q4-1989Q1 1998Q3-2003Q1 2007Q1-2010Q1 2016Q1-2019Q4	62	1992Q2-1995Q4	15

In the residential property market, three bubble periods were identified. The first one occurred in the late 1980s. According to Ball (1994), this property boom was caused by "market madness watched over by misguided governments" (p. 671). In a nutshell, it was a result of over-optimism caused by the huge economic recovery after the recession in the early 1980s, financial liberalisation, the boom in the service sector, and lack of regulation (Ball, 1994). The second period was detected between the end of 1998 and the crash of the housing market in 2008 that ignited the Great Recession. The extremely high value for the BSADF statistics over this bubble period is consistent with the fact that the recent financial crisis was mostly caused by a sharp fall in the housing market after years of price excessiveness and appreciation. Finally, the results show that the U.S. markets are currently facing a bubble in the residential market. Albeit still on a smaller scale compared to the previous one, this finding emphasise that policymakers should be alert, as housing bubbles may lead to banking crises, as already highlighted previously. Therefore, after its collapse in 2008, the results show that the housing market is again experiencing price excessiveness, however, different from the previous housing bubble, it has not been accompanied by a bubble in the household credit market. In constrast, in the commercial property segment, only a crisis period was detected. This episode is in line with the economic recession that happened in the U.S. in the early 1990s. Moreover, a bubble period was identified over 2006-2007 but it was a very short-lived episode and so was not included in Table 2. Note that these results reinforce the interest of considering different segments of the real estate market, as bubble-like behaviour was found in fifty-nine quarters in the residential property segment against no evidence of bubble episodes in the commercial one.

In the credit market, the different segments also experienced different bubble periods. Therefore, considering a segmentation of the credit market also allows us to say more about where bubbles are coming from in this specific market. The procedure identified two bubble episodes in the log credit to households as a percentage of GDP. The first episode occurred over 1985-1992 and was caused by great ease of credit constraints during the financial liberalisation process over the 1980s (Ball, 1994). The bubble burst during the economic recession in the early 1990s. The second period identified is consistent with the argument of, for instance, Jordà et al. (2015), that the Great Recession was triggered by a housing bubble reinforced by rapid credit growth granted to "subprime" households. Note that the bubble detection test determined that the bubble burst only in 2010, which reveals that the credit market reacted with a lag to the crash in the financial markets. Also, this market is the one that experienced more quarters in which a bubble was detected (73 in total). Furthermore, as emphasised by Gómez-González et al. (2018), the results of the bubble detection tests require careful analysis. Although the procedure detected a crisis period over 2011Q3-2019Q4, analysing the behaviour of the log household credit-to-GDP (Panel (E) of Figure 1), this period looks more like normalisation from a huge increase of the household credit during the build-up phase of the Great Recession than a crisis episode. Therefore, this period will not be considered as a negative bubble.

Finally, regarding credit to non-financial corporations, the periods that were mentioned before in the analysis of the time series (subsection 3.2) were identified as bubble periods. Thus, four different episodes were detected, which is a larger number in comparison with the other markets. In particular, there is evidence of an ongoing bubble that started in 2016, contrasting with a decreasing trend in the credit to households since 2010. A negative bubble was also identified over 1992-1995.

The results above suggest that some markets experienced more periods (read more quarters) in which a bubble was detected than others, namely the housing market, credit to households, and credit to non-financial corporations, as evidenced in Table 2. This conclusion highlights the importance of monitoring these markets or segments to early warn for a forthcoming financial crisis. This is line with Anundsen et al. (2016) and Büyükkarabacak and Valev (2010) as they considered bubbles in these markets, and particularly these segments, as the most relevant early warning indicators of banking crises. A possible explanation for founding less evidence of bubble-like behaviour in the stock market and the commercial property market is the fact that these markets are mostly operated by more sophisticated investors, that is, the more unsophisticated the agents are, the more prone to bubbles a market may be (Scherbina & Schlusche, 2014). Also, the bank stock market may not be representative of the whole banking system since many banks are not publicly listed, which may be another potential explanation for observing fewer bubbles in the bank stock market.

In sum, two main conclusions should be highlighted: first, the housing market and credit to non-financial corporations are currently undergoing a bubble episode; and, second, considering the segmentation suggested allows us to say more about where bubbles are coming from in each market. This knowledge is particularly relevant for tracing the contagion effects to be pursued in the following subsection.

3.3.2 Bubble Contagion: From Core to Receptor

This subsection will test whether the bubbles identified previously spread to other markets.

From the results of the bubble detection tests above, three markets are identified as potential core markets for these bubble contagion tests. To this end, I focus on markets where more and longer bubble periods occurred, that is, the housing market, credit to household, and credit to non-financial corporations. The non-financial stock market was not regarded as the core market since only one bubble episode was detected ("dot-com" bubble). If this was the market where a bubble might originate, the other bubble periods in the other markets remain unclarified, because they were not preceded by a bubble in the non-financial stock market.

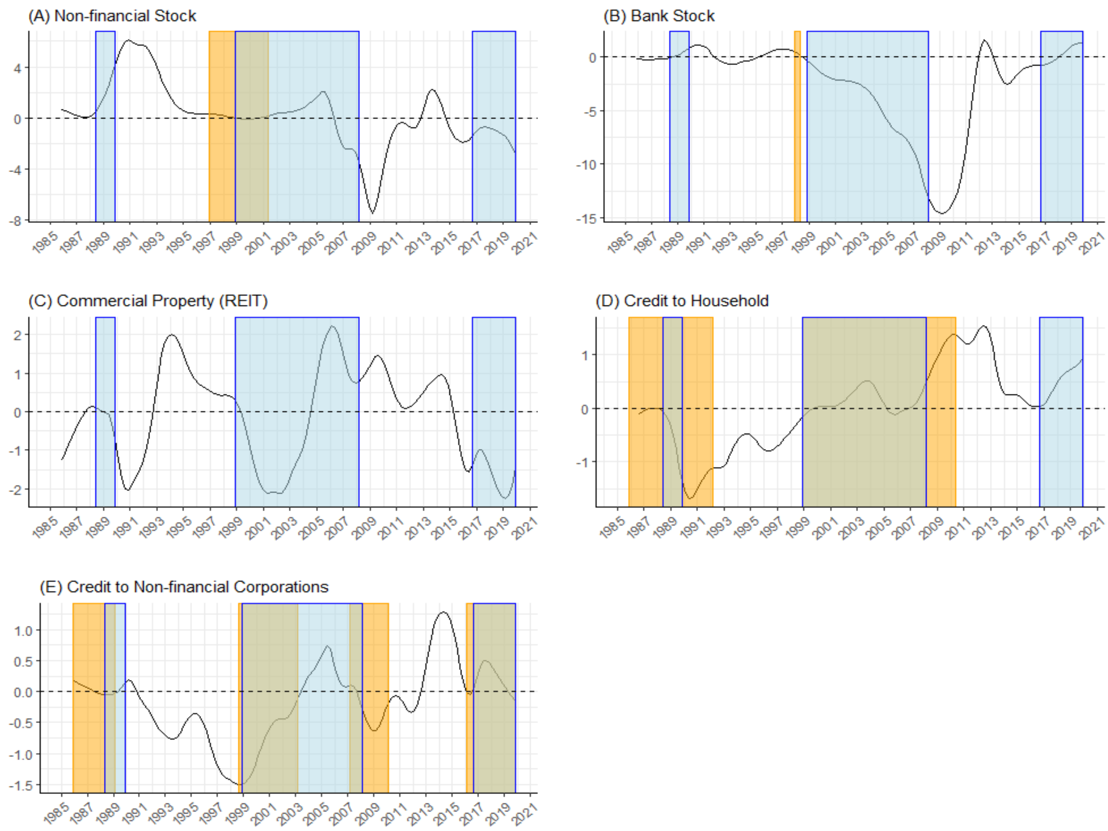
For the bubble contagion analysis, the residential market is taken as the core market for three reasons. First, focusing on the most harmful bubble period since the Great Depression, i.e. the early 2000s, a bubble-like behaviour started first in the housing market (1998Q4) and was more pronounced here than in the household credit market (2001Q2).[43] Although an explosive movement appeared one quarter earlier in the credit to non-financial corporations (1998Q3), since this bubble burst in 2003 and another started in 2007, such timing suggests that the former was more related to the "dot-com" bubble period in the stock market than to the bubbly economic conditions which precipitated the Great Recession. Second, as emphasized by Büyükkarabacak and Valev (2010), possible deviations in the credit market are amortized over many years, while other markets, such as the housing market, may experience a rapid correction. This is confirmed by a finding of the present work that bubbles in the credit markets only burst in 2010 and, conversely, the bubble in the residential market burst in 2008. For the reasons mentioned above, the credit market does not seem to be a suitable core market. Third, the burst of housing bubbles is inevitably related to the emergence of deep financial crises (e.g. Anundsen et al., 2016). Thus, inspecting if there are contagion effects from a housing bubble to other markets is relevant as it may cause the collapse of the financial system, as occurred in the recent financial crisis.

As explained before, the estimate of the contagion coefficient that evaluates whether there is bubble contagion between markets is conducted through a smoothing procedure. Therefore, the analysis of the results should bear in mind that the increase in the sensitivity of one market to another as evidence of bubble contagion may only appear in a very smooth way (Deng et al., 2017). Also, the analysis is focused on bubble contagion and so only positive bubbles will be considered hereafter.

[43] As the bubble started at the same time in the housing and household credit markets considering 90% critical values (1998Q4), the analysis was conducted using 95% critical values to define which bubble begins first and have a steeper movement.

Figure 3 depicts the estimate of the time-varying contagion coefficient of equation 3.8. that allows us to inspect the contagion of explosive behaviour from the housing market to the other markets. The interconnectedness between housing and stock markets has been widely explored in the literature, as reviewed in chapter 2. However, the results shown in the panel (A) of Figure 3 demonstrate that not only these markets are interconnected but more precisely explosiveness in the residential market may transmit to the non-financial stock market.

Figure 3. Bubble contagion from residential property market



Notes: Blue shaded areas are bubble periods detected in the core market (in this case, the housing market) and orange shaded areas are bubble episodes identified in the recipient market at a 10% significance level.

During the first two bubble episodes in the housing market, the contagion coefficient is positive and increases over the bubble periods. Also, an inverted U-shape is observed in the contagion coefficient, which provides strong evidence that the explosive behaviour in the housing market transmitted to the non-financial stock market. Note that during the housing bubble in the early 2000s, the contagion coefficient peaks between the end of 2005 and the beginning of 2006 which is precisely when the log price-to-rent reaches the peak (Figure 1), consistent with the evidence of bubble contagion over this episode. However, a bubble in the non-financial stock market was not detected after a housing bubble. In fact, a stock bubble was only identified during the "dot-com" period and hence a further analysis will be done in subsection 3.3.3 to clarify if bubble contagion was a cause of the stock bubble over the end of the 20th century. During the last bubble episode in the housing market, the contagion coefficient is negative, indicating a negative impact on the stock market. As pointed out by Ali and Zaman (2017) and Gómez-González et al. (2017), this may be due to the expectation formation effect, as while prices in the housing market are increasing and investors expect that they will continue the upward movement, investing in this market is a profitable decision and so more and more investors invest in the housing market rather than in the stock market.

Regarding the bank stock market, evidence of bubble contagion is found only for very short periods, in particular during the housing bubbles of 1988-1989 and 2016-2019, in which the contagion coefficient is positive and is increasing during the bubble periods. However, the result that stands out the most is the negative value and decreasing movement in the contagion coefficient over the housing bubble in the early 2000s. This highlights that not only the housing bubble does not transmit to bank stocks but especially it produces an adverse reaction on bank stocks. Probably, this is due to the fact that banks do not have incentives to ride bubbles (Aoki & Nikolov, 2015). Their main activity is very profitable by exploring the loan-deposit rate spread and so returns of investing in overvalued assets do not compensate for the risk of a huge loss when the bubble bursts (Aoki & Nikolov, 2015; Wang, Chen, & Xiong, 2019). Therefore, other core markets will be considered later to explain exuberance contagion to the banking sector.

As expected, there is strong evidence of bubble contagion from the residential real estate market to the commercial segment, as the coefficient is positive during large periods (as can be seen in panel (C) of Figure 3). The coefficient increases significantly and exhibits an inverted U-shape during the second housing bubble, which led to a very short-lived bubble in the commercial property market over 2006Q4-2007Q1.[44] Note that the estimated coefficient decreases just after each housing bubble starts but then increases sharply. A possible explanation is that these markets are close substitutes and so when a bubble emerges in the residential segment, investors adjust their portfolios and invest more in the overvalued housing market in the search for profitable returns, expecting prices to continue to increase. Therefore, the negative part of the coefficient may be explained by investors going from the

[44] Not represented in the graph, because the bubble does not last for at least three quarters

commercial to the residential (to ride the bubble) causing prices in the commercial to react in an opposite manner. However and notwithstanding the foregoing, a housing bubble ultimately transmits to the non-residential segment. The contagion coefficient starts increasing approximately three years after the beginning of the housing bubble as investors in the residential segment start realising that the housing market is experiencing excessiveness and the bubble may burst soon. Then, agents redirect their investments from housing to the commercial segment as exuberance has not yet been experienced there, which causes the upturn in the contagion coefficient.

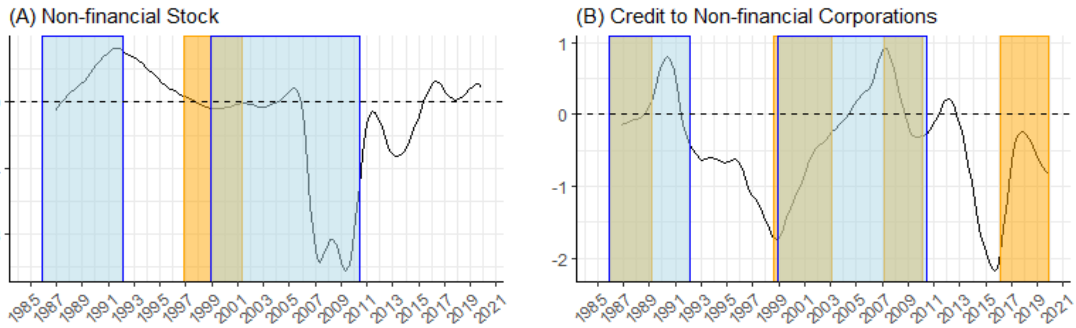
The contagion from the housing market to the credit markets is particularly evident during the housing bubble in the early 2000s, in which the coefficient exhibits an inverted U-shape. In the credit to non-financial corporations, the coefficient starts increasing precisely when the bubble emerges in the housing market and peaks a few quarters before the emergence of a credit bubble in 2007, which provides evidence of bubble contagion. Bubble contagion to this market is also detected over both the first and last housing bubbles. While the connection between these markets has already been studied in the literature (as shown in subsection 2.4.1), this is the first study testing it with this methodology, which contributes to empirically confirming the linkage between them. Regarding the credit to households, the coefficient peaks in the middle of the housing bubble, which is consistent with a reciprocal reinforcing movement between these two markets that fuel one another (e.g. Agnello & Schuknecht, 2011; Arestis & Gonzalez, 2014).[45] However, the positive coefficient at the end of the sample period should not be considered as evidence of bubble contagion since a bubble was identified in the housing market but a crisis period was detected in the household credit.

Furthermore, analysing the housing bubble in the early 2000s, the contagion coefficient peaks first in the credit to household and then in the non-financial stock market and credit to non-financial corporations. More than that, after the peak in 2004, the coefficient in the household credit reaches a trough precisely when a peak is observed in the coefficient of the other two markets. These results suggest that the housing bubble may have transmitted to the stock market through an indirect channel. More precisely, first, the bubble transmits to the credit market and then to the stock market, which may result from the role of the collateral channel in explaining bubble contagion from the housing market to the stock market, as explored in subsection 2.4.3. In order to explore this view, contagion tests have

[45] The other side of this bi-directional relation is going to be explored in the following subsection.

been applied considering credit to households as the core market and the non-financial stock market and credit to non-financial corporations as the receptors. The results are presented in Figure 4. The results are in line with the argument presented above, as evidence of bubble contagion is found. In other words, since both of these contagion coefficients depicted in Figure 4 reach a local maximum around the peak in the coefficient of the bubble contagion test from the housing to the non-financial stock market presented in Figure 3, bubble contagion from the housing to the non-financial stock market may be the result of the ease of access to credit after the increase in the housing prices used as collateral. Therefore, these results support the view that the collateral channel may be a mechanism through which housing bubbles transmit (indirectly) to the stock market.

Figure 4. Bubble contagion from household credit market



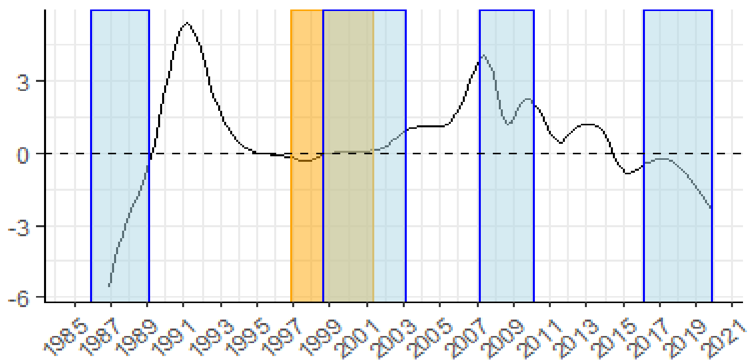
In sum, in addition to the literature on the relevance of housing bubbles to the likelihood of banking crises referred to previously, the results presented in this subsection highlight that bubbles in the residential market may transmit to the stock and credit markets potentially reinforcing a self-fuelling cycle that boosts bubble-like behaviours in these markets. In particular, two periods of contagion should be outlined. First, during the period preceding the recent financial crisis, the housing bubble spread to the other markets, except for the banking sector, in which a negative reaction occurred. Second, there is evidence of bubble contagion from the housing market to credit to non-financial corporations for the current ongoing bubbles in these markets, which emphasises the importance of considering different segments of each market. Note that this is the first study that uses this methodology to study the linkages between these segments of these three crucial markets for financial stability.

3.3.3 Additional Analysis: Exploring Other Contagion Movements

As referred to in the previous subsection, some linkages remain to be clarified. Although some evidence of bubble contagion from the housing to the non-financial stock market is found, the "dot-com" bubble was not motivated by exuberance in the housing market.

Therefore, this section starts by exploring (Figure 5) whether there is bubble contagion from the credit to non-financial corporations to the stock market, as suggested in subsection 2.4.2.

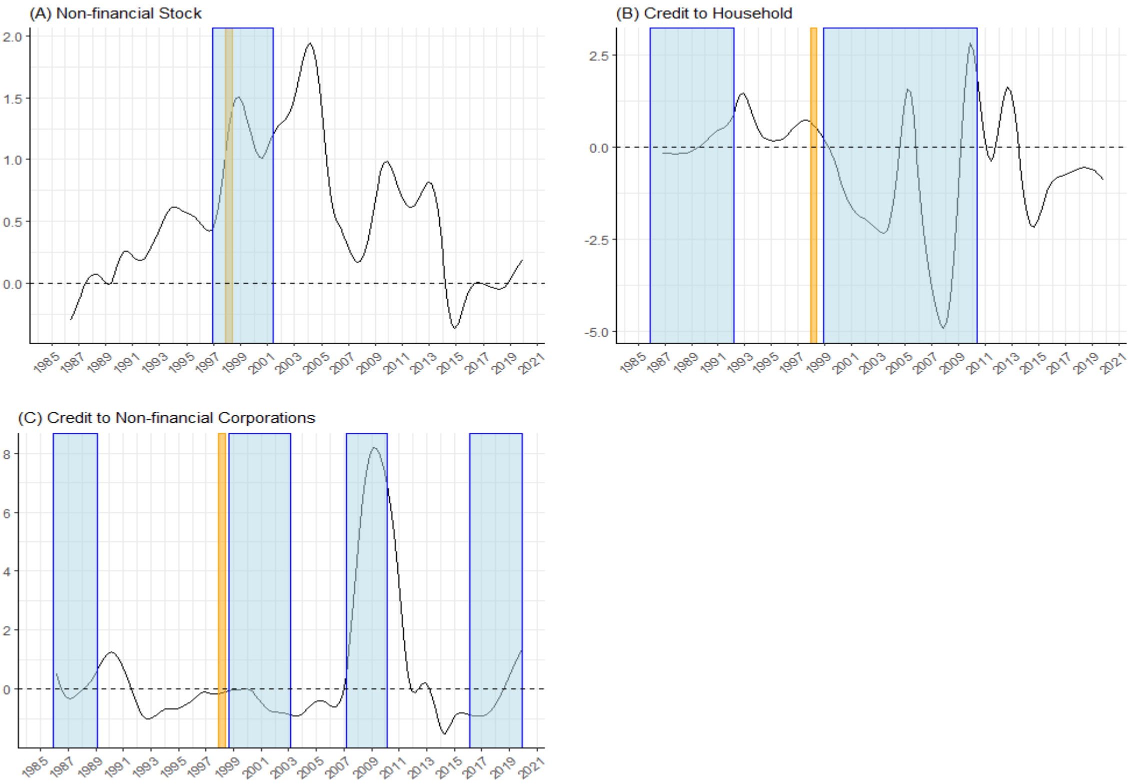
Figure 5. Bubble contagion to non-financial stock market



In fact, exuberance in credit to non-financial corporations transmits to the non-financial stock market. This is particularly noticeable for the period 1999-2008 in which the coefficient exhibits an increasing movement and an inverted U-shape that peaks when the stability of the financial system has come under threat in 2008. However, the behaviour of the coefficient at the beginning of the "dot-com" bubble suggests an absence of bubble contagion, which means that this period was not motivated by the transmission of exuberance from other markets and so may have been a result of irrational optimism surrounding a novel technological improvement, on the basis of the results of Zeira (1999).

Bank stock prices do not seem to be prone to bubbles as exuberance was detected only for three quarters. However, the Great Recession highlighted the vulnerability of the banking system to bubbles in other markets, such as the housing and credit markets. In the previous analysis, only little evidence of bubble contagion was found from the residential market to bank stocks. Figure 6 completes the previous analysis of how vulnerable banks' stock valuation is to bubbles in other markets. Panel (A) shows that bank stocks follow closely the movement in the non-financial stock market, that is, evidence of bubble contagion from the non-financial stock market is found. Therefore, exuberance in the bank stock market is more associated with stock bubbles than bubbles in the housing market. The household credit market also transmits explosive movements to bank stock prices as the coefficient behaves accordingly (i.e. positive and increasing coefficient with an inverted U-shape during bubble periods). Evidence of bubble contagion is also found from the credit to non-financial corporations mostly during the bubble period that started in 2016. Note that although the coefficient is extremely positive over 2007-2009, one should not consider it as evidence of bubble contagion, as a positive bubble is found in the credit to non-financial corporations but a crisis period is detected in the bank stock market, as referred to in subsection 3.3.1.

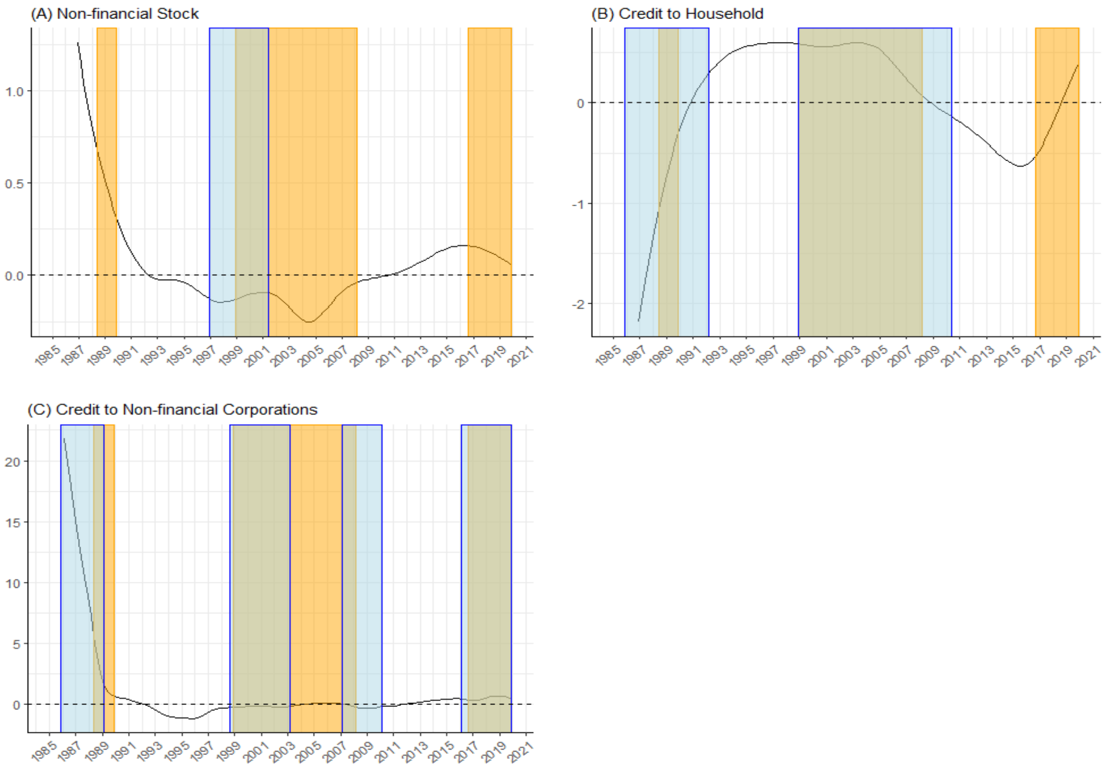
Figure 6. Bubble contagion to bank stock market



Although the housing market was considered as the core market in the main analysis for the reasons presented before, it is also important to understand if this market is exposed to bubble contagion from other markets. We saw, for instance, that every housing bubble detected in the present work was preceded by a bubble in the credit to non-financial corporations, which begs the question of potential contagion from this market.

Figure 7 depicts the estimate of contagion coefficients from the non-financial stock market, credit to household, and credit to non-financial corporations to the housing market. The contagion coefficient denotes a similar behaviour from the non-financial stock market and from credit to non-financial corporations to the housing market. Evidence of transmission from these two markets is only found at the end of the sample period, in which a positive coefficient is observed, and so they are not identified as relevant markets triggering housing bubbles. In turn, the credit to households is deeply linked to the housing market, as the coefficient is positive and exhibits an inverted U-shape between the first two bubble periods. This finding of contagion from household credit to the housing market in the global financial crisis should be now combined with the finding of contagion in the opposite direction found in the previous subsection. This bi-directional link is key for understanding this crisis, as increasing housing prices ease the access to credit, and, in turn, rapid credit growth allows subprime households to acquire residential assets, putting the financial system in danger, as pointed out, for instance, by Claessens, Ayhan Kose, et al. (2010). Note that this is the first study that reaches these conclusions about the Great Recession using this methodology.

Figure 7. Bubble contagion to residential property market



These conclusions support the theoretical understanding that the stock market is more related to credit to non-financial corporations and the housing market is more linked to household credit, as referred to in subsection 2.4. While evidence of bubble contagion was also found from the housing to the non-financial stock market, the credit market potentially has a role in that connection, emphasising the importance of the collateral channel for bubble transmission. Moreover, the current ongoing bubble in the housing market is receiving contagion from the current ongoing bubble in credit to non-financial corporations, and so these bubbles are mutually reinforcing each other as we also found evidence of bubble contagion in the opposite direction in the previous subsection. Finally, the current bubble in credit to non-financial corporations is transmitting to bank stocks (as can be seen in panel (C) of Figure 6), which is also currently receiving contagion from non-financial stocks.

4 Concluding Remarks

The present work carries out an analysis to detect the occurrence of bubbles in segments of the stock, real estate, and credit markets and to detect contagion between them. To this end, the methodological framework proposed by Phillips et al. (2015) was implemented to detect bubble episodes in U.S. quarterly data over 1980Q1-2019Q4. Then, tests of bubble contagion were conducted following the methodology developed by Greenaway-McGrevy and Phillips (2016) in order to analyse if bubbles transmit between these markets.

The main findings of the bubble detection tests are threefold. First, some markets stand out as experiencing more quarters in which a bubble was detected than others, namely, the housing market and the two segments of the credit market, though bubbles in the credit to non-financial corporations are of shorter duration than those of the housing market and household credit. Conversely, bubbles in the stock market are quite infrequent, possibly because this market is mostly operated by more sophisticated investors. Furthermore, from the analysis by segments, the results show that some of them may induce more vulnerabilities than others. For instance, within the real estate market, the housing market experienced more bubble periods than the commercial property segment. Also, the bubble in the non-financial stock market is more significant than the bubble detected in bank stocks. Second, the residential property market exhibits the highest value of the test statistics, signalling a huge housing bubble in the early 2000s that peaked before the beginning of the Great Recession. Moreover, note that during 1998-2008 at least one bubble episode was detected in all markets (except for the commercial property market in which only a short-lived bubble was identified), reinforcing the idea that this period was remarkably distinctive. Third, the results reveal that the housing market and credit to non-financial corporations are currently undergoing a bubble period.

The results of the bubble contagion analysis provide evidence of bubble contagion from the housing market to all the other markets (more pronounced in the commercial property and household credit markets), which is particularly significant during the build-up phase of the Great Recession. Moreover, not only evidence of bubble contagion to the non-financial stock market was found, but also the results reveal that housing bubbles may transmit to the stock market through the credit market, which suggests an important role of the collateral channel in explaining the bubble contagion from the housing market to the non-financial stock market. Furthermore, bubbles in the residential market are more related to bubbles in the credit to households and stock bubbles are more related to exuberance in credit to non-financial corporations. Bank stock prices are mostly driven by the stock market, though the credit market has some positive influence. Finally, the current ongoing bubbles in the housing market and credit to non-financial corporations are mutually reinforcing each other as evidence of bubble contagion in both directions was found.

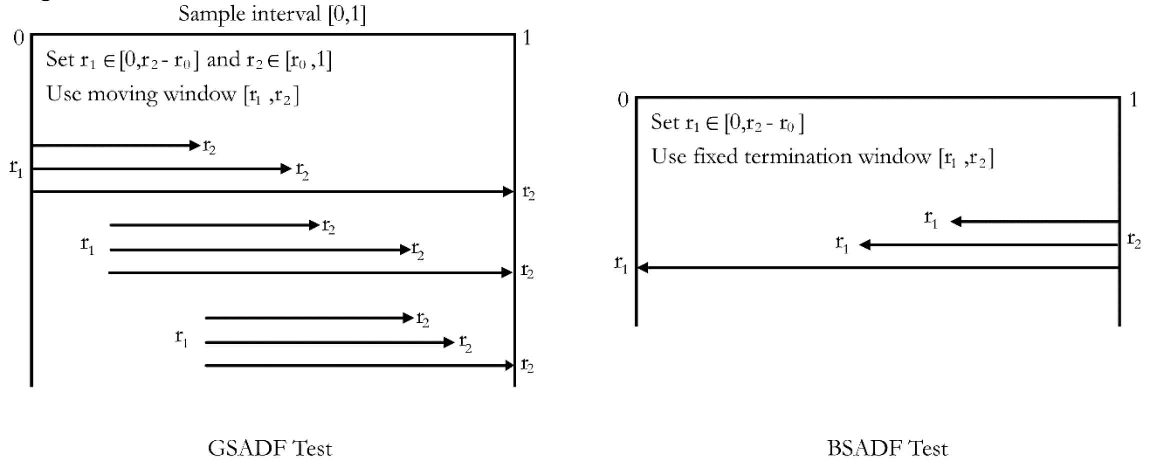
The findings summarised above have important implications for both policymakers and investors. On the one hand, considering that bubbles, more specifically housing and credit bubbles, are suitable predictors of financial crises, the results of the present work suggest that policymakers should monitor the performance of these markets, as these are precisely the markets in which more bubble periods occurred, which means that either they are more prone to bubbles or bubbles in these markets are of longer duration and magnitude. Also, evidence of bubble contagion from and between these markets was found. Therefore, these findings may contribute to the literature that advocates that central banks should "lean against the wind" to prevent a financial collapse resulting from the burst of multiple bubbles that reinforce each other. Additionally, the results highlight the need for the development of macroprudential policies for limiting the potentially harmful consequences of a financial crisis. On the other hand, these results are potentially relevant to investors' decisions. For instance, knowing that housing bubbles transmit to the stock market has implications for risk management. Also, if a bubble appears in the household credit market, the results suggest that investors may expect the emergence of exuberance in the housing market as well.

However, like all research works, the present dissertation leaves room for further research. First, the analysis was only conducted for the U.S. markets. Although the U.S. has one of the most developed financial systems, a further investigation on these topics may include other countries to check for the robustness of these findings. Second, bubble contagion may occur either across different assets or from a cross-border perspective. Therefore, analysing the international transmission of bubbles in these markets may be the next step to understand the emergence of exuberance among these markets. Third, the same analysis can be applied to other assets and markets or even to a different segmentation of the markets under analysis. Particularly, data is available for more sectors of the stock market and so it might be interesting to explore bubble contagion between all different sectors of the stock market. Finally, the present work does not propose to formally test for causality, for example, through the Granger test, which may be a complementary work.

5 Appendix

Appendix A1

Figure 8. Illustration of GSADF and BSADF tests



Adapted from Phillips et al. (2015)

Appendix A2

The bandwidth parameter h is estimated according to a cross-validation approach. For a given d, the optimal bandwidth is obtained as follows:

5.1. $$\check{h}_{jT}(d) = \arg \min_{h \in H_T} \sum_{s=S}^{T} \left\{ \tilde{\beta}_{j,s} - \check{\gamma}_j \left(\frac{s}{T-S+1}; h, d \right) \tilde{\beta}_{core,s-d} \right\}^2,$$

where $H_T \in \left[(T-S+1)^{-\frac{1}{2}}, (T-S+1)^{-\frac{1}{10}} \right]$ and

$$\check{\gamma}_j \left(\frac{s}{T-S+1}; h, d \right) = \frac{\sum_{p=S, p \neq s}^{T} K_{hp} \left(\frac{s}{T-S+1} \right) \tilde{\beta}_{j,p} \tilde{\beta}_{core,p-d}}{\sum_{s=S}^{T} K_{hs} \left(\frac{s}{T-S+1} \right) \tilde{\beta}_{core,p-d}^2}$$

However, $\check{h}_{jT}(d)$ depends on the lag order d. Therefore, the optimal delay parameter d is estimated in order to minimize the mean squared error of the equation 3.11. such that

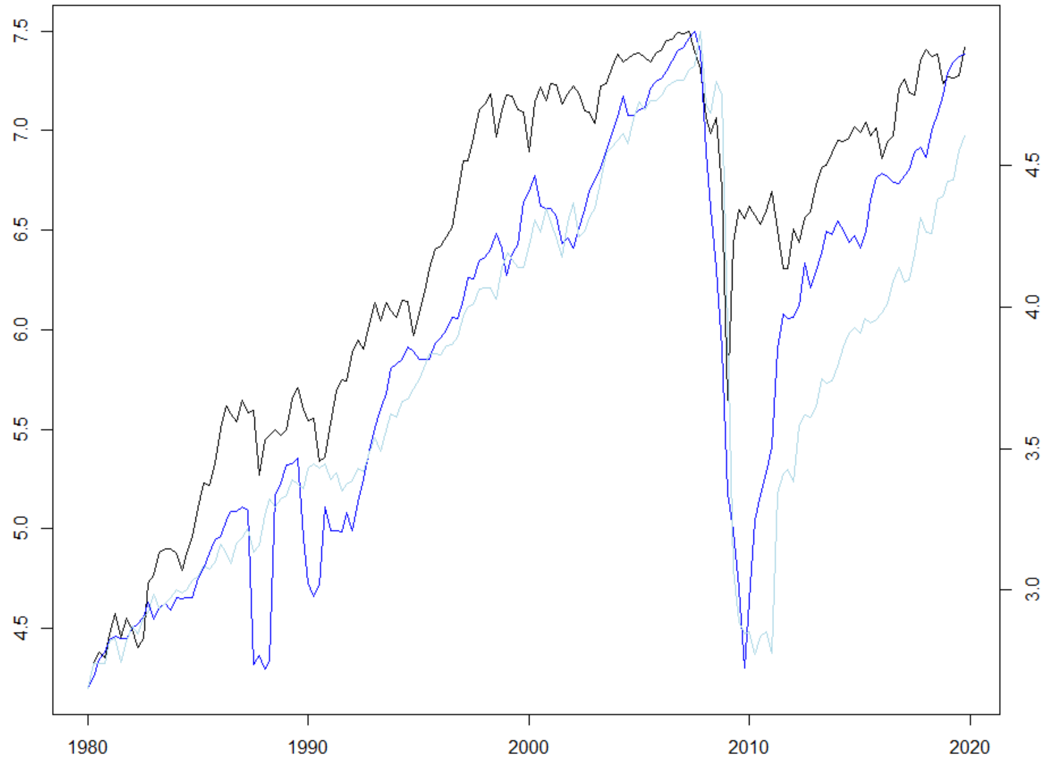
5.2. $$\check{d} = \arg \min_{d \in \{0,1,\ldots,4\}} \sum_{s=S}^{T} \left\{ \tilde{\beta}_{j,s} - \check{\gamma}_j \left(\frac{s}{T-S+1}; \check{h}_{jT}(d), d \right) \tilde{\beta}_{core,s-d} \right\}^2,$$

where $\check{\gamma}_j \left(\frac{s}{T-S+1}; \check{h}_{jT}(d), d \right)$ is the leave-one-out estimator with the optimal bandwidth.

Considering these formulations, it is obtained a bandwidth and lag parameter, that minimize the mean squared error for each equation of the form 3.11.

Appendix A3

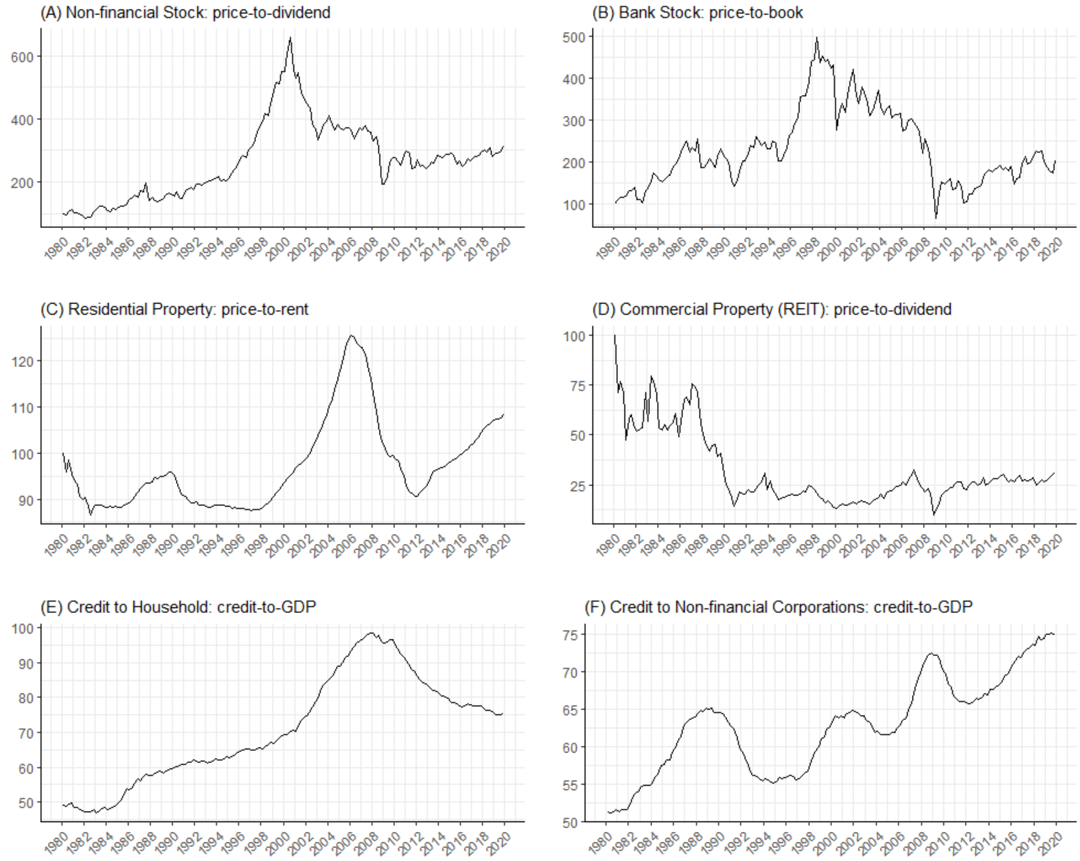
Figure 9. Bank stock price, dividends, and earnings



Notes: The black line refers to bank stock prices (left axis). The dark and light blue lines depict dividends and earnings, respectively (right axis). Note how the drop in dividends and earnings is much more pronounced than in bank stock prices over 2008-2009.

Appendix A4

Figure 10. Price-to-fundamental ratios by market (in levels)



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